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**Modeling Skill Growth and Decay in Edge
Organizations: Near-Optimizing Knowledge &
Power Flows (Phase Two)**

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Paper Title: Modeling Skill Growth and Decay in Edge Organizations: Near-Optimizing Knowledge & Power Flows (Phase Two)

*(Student Paper)

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Modeling Skill Growth and Decay in Edge Organizations: Near-Optimizing Knowledge & Power Flows (Phase Two)

Abstract

This paper outlines efforts to model, simulate and ultimately optimize knowledge flows in Edge organizations. We begin by reviewing Phase I research which explored how *knowledge inventory* flows through organizations, analogously to perishable, physical goods inventory in a supply chain, and uncovered useful insights to clarify current understanding and permit initial quantification of knowledge management impacts on organizational performance. Current Phase II efforts are then described that classify, quantitatively model, and simulate knowledge flows within and among individuals in Edge organizations. Empirical, experimental data on rates of learning and forgetting drawn from the social and cognitive psychology literature provide the basis for defining and modeling agent learning and forgetting micro-behaviors in our POW-ER computational simulation model of organizations. Phase II (micro-level skill acquisition) builds on Phase I (macro-level inventory control) by modeling the trajectories of individual knowledge flows associated with dynamic knowledge inventory increases and decreases. Using this model, we conduct intellectual experiments (using models of idealized work processes and organizations) and emulation experiments (to replicate outcomes of real work processes and organizations) for model refinement and validation. The goal of these experiments is to determine organizationally, contingently optimal knowledge intervention strategies. Cumulative Phase III efforts are introduced that integrate findings from prior phases to “engineer” knowledge management solutions in organizations via a *Knowledge Chain Management* approach.

Introduction and Motivation

Edge organizations [1] can only achieve their putative effectiveness through the thoughtful management of knowledge. For instance, Alberts and Hayes implement the term *agility* to encompass the facets of *robustness*, *resilience*, *responsiveness*, *flexibility*, *innovation*, and *adaptation*. For each of these Edge-like qualities to exist, the flows of knowledge among individuals and its contextual deployment to support *shared awareness* and *self-synchronization* in Edge organizations must first be explored, understood and managed. Toward this goal, our efforts are offered in Phases I, II, and III. Phase I explored *knowledge inventory* [34]. In this phase we considered knowledge as a perishable set of skills like physical goods. Using proven mathematical management science formulae and methods such as Economic Order Quantity (EOQ) and cost analysis, as well as inventory doctrines of Just-In-Case (JIC), Just-In-Time (JIT), and make vs. buy decisions, we examined knowledge flows using the metaphor *perishable inventory* with some success. We closed by introducing the novel concept *knowledge chain management* via theoretical modeling. In Phase II we refine this effort through research described in the present article by considering cognitive learning and forgetting rates. We model and test mechanisms for changing the level of participants’ knowledge by collating available experimental data in the social and psychological literature, and by observing knowledge workers in Edge organizations. This effort more precisely informs our knowledge of growth and decay, and can be used within the Knowledge Inventory modeling of Phase I. Phase III then looks forward by determining contingently optimal knowledge flows in different organizational contexts through developing a more precise methodology for *Knowledge Chain Management*.

Background – Phase I Review

A large body of research exists on *information* flow in organizations, going back to the pioneering work of Herbert Simon in the 1950’s [53]. However, the corresponding literature on the flow of *knowledge* in organizations is only just emerging (e.g. [33, 41, 44]) and remains inchoate. To gain theoretical insight into knowledge (and therefore power) flows, we began our research efforts in Phase I by describing knowledge as a set of skills that grow and decay over time due to different environmental effects. We sought to understand how such skills can be managed to maintain efficiencies required for edge-like qualities such as *agility* and *robustness*. Specifically, as noted above, we posited a model of *knowledge as perishable inventory*, whereby we

discussed how parallel losses occur with respect to knowledge as a result of phenomena such as employee turnover, knowledge decay, and obsolescence, and how they aligned with perishable, physical goods. Table 1 below pairs phenomena of knowledge interventions with their perishable physical goods counterparts.

Table 1. Knowledge vs. Perishable Goods

Phenomena	Knowledge Intervention	Physical Goods Counterpart
Additions (inflows)	Mentoring	Custom production (make)
	Formal training	Job shop production (make)
	On-The-Job Training	Assembly line production (make)
	Personnel transfer	Custom order (buy)
Subtractions (outflows)	Employee turnover	Demand
	Knowledge Decay	Perishability
	Obsolescence	Obsolescence
Holding costs	Diffusion benefit	Security, refrigeration, etc.
Optimal Ordering	EOQ	EOQ
Inventory System Operating costs	(about the same)	(about the same)
Operating Doctrines	JIT/JIC	JIT/JIC

We combined this framework with the proven mathematical formulae used in management science inventory control to explore how we might adapt methods to determine costs of knowledge inventory additions (i.e., knowledge inflows), subtractions (i.e., knowledge outflows), reordering as well as Economic Order Quantity (EOQ) decisions, holding costs, inventory doctrines of Just-In-Case (JIC), Just-In-Time (JIT), and make vs. buy decisions. Each of these elements is explained briefly and in turn.

Knowledge Inflows

Knowledge inventory represents the *stock* of knowledge [Dierickx and Cool, 1989] possessed at any point in time by people, groups and organizations. We say, “at any point in time,” to acknowledge expressly the dynamic nature of knowledge—and hence knowledge inventory—which is flowing constantly in and out (i.e., causing additions to and subtractions from knowledge inventory). Knowledge flows derive from a relatively small set of organizational processes and environment effects [41]. For instance, knowledge inflow processes include mentoring, classroom training, and On-the-Job Training (OJT; i.e., trial and error learning). Each such inflow process serves to increase knowledge inventory, but at different rates and with different characteristics. More specifically, mentoring provides relatively quick and personalized feedback on errors as well as individually tailored instruction, thus potentially enabling faster learning at the individual and (very small) group levels. It also has beneficial effects in both tacit and explicit dimensions based on assiduous mentor contact. However, mentoring is costly; it assumes that more knowledgeable employees are available, willing, and capable of serving as mentors, and that the organization can function temporarily without them, as they defer their own work tasks in order to provide assistance to others. A cost is also incurred as a mentor’s tacit knowledge is converted into explicit knowledge, because of the incomplete or “filtered” nature of the exchange [46]. Hence mentoring, as with every knowledge inflow process, involves both costs and benefits, which the informed leader or manager must tradeoff—explicitly or implicitly—when deciding which to use, when, and how often.

Alternatively, employees may be formally trained (e.g., in a classroom setting). The classroom training inflow process would offer its own, unique mix of costs and benefits. For instance, relatively large groups of people can be trained simultaneously in the classroom, whereas mentoring is limited to one-on-one or one-on-few modes. However, people must generally leave their workplaces—and hence stop working productively—while participating in classroom training, whereas the person being mentored works directly on job tasks. The informed

leader or manager must consider such tradeoffs when assessing the relative merits of assigning mentors versus sending employees to school for classroom training. Additionally, as implied by the name, the alternate knowledge inflow process of OJT involves instead each employee learning simply and directly while on the job. This process involves relatively slow accumulation of perfunctory knowledge—seen most often, and understood most easily at the individual level—and has been confirmed empirically through learning curves (e.g., see [Argote et al., 1990 and Wright 1936]) to result in many errors along the way, particularly in the early phases of learning by doing.

Knowledge Outflows

Second, knowledge flows out of people, groups and organizations also. Such outflows represent subtractions from knowledge inventory, and arise from knowledge outflow processes such as employee turnover, knowledge decay and knowledge obsolescence. More specifically, employee turnover causes all tacit knowledge of transferred employees, for instance, to flow completely out of the transferring organization. As with the alternate knowledge inflow processes described above, *employee turnover*—used generally as a negative or pejorative term—has costs as well as benefits also. For instance, turnover costs can include losses of productivity due to work disruption, reductions in organizational learning and memory due to tacit knowledge outflows, and search costs associated with identifying, recruiting and transferring one or more replacement employees. Benefits can include introducing new ideas and fresh perspectives to the organization, promoting tacit knowledge flows between organizations, and broadening the experience bases of employees who change jobs. Moreover, such costs and benefits are amplified in proportion to the number and frequency of personnel transfers, as well as the level of social aggregation involved. For instance from the Military, in addition to transferring individual people to and from organizational units and commands, it remains common practice to transfer whole units (i.e., relatively large groups and teams) into and out of different commands (i.e., large organizations), and to even change entire command organizations during the middle of military operations (e.g., consider the planned, periodic rotation of Carrier Strike Groups and Expeditionary Strike Groups who support operations in Iraq today).

Knowledge decay at the individual level—and arguably also at the group and organization levels—occurs on a much slower scale than employee turnover and is caused by two phenomena – *time* and *interference* [2]. The rate at which forgetting occurs increases with skill complexity and time delay since last performed. *Interference* considers the number of other tasks that have been accomplished between target events of interest, bumping out portions of the original knowledge that competes for the same memory resources. For instance these two knowledge outflows can occur as a worker spends more time accomplishing one task while neglecting another. And as the second task becomes necessary to perform, it may suffer from a lengthy delay of disuse and may be difficult to recall because of the routine performance and cognitive requirements of the first skill. In a military setting, bridge watch standing takes place every day whereas anti-submarine warfare occurs infrequently. The second skill may suffer from knowledge decay due to disuse, and may also suffer from interference due to well-practiced and memorized mathematical routines necessary to perform the first skill.

Finally, knowledge *obsolescence* is a form of knowledge decay due to a growing field or environmental uncertainty. What was once current knowledge is now outdated and must be refreshed and augmented. This can require ever increasing levels of inventory and frequency of re-supply to keep pace with the growing field of available knowledge, and has the appearance and effect of a knowledge outflow due to decay. Rapidly advancing, technological fields such as software engineering and biomedical research represent vivid, current examples.

Holding Costs

Within the physical realm, holding costs are associated with maintaining items in inventory, such as security, air-conditioning, and maintenance. However, explicit and tacit forms of, knowledge - considered as perishable goods - sometimes exhibit a different set of holding costs. For instance, when compared to that of most physical goods, the marginal cost of adding, duplicating and disseminating explicit knowledge is very low (if not zero). However, in its tacit form, knowledge is much more nebulous to guard and maintain, since it resides in the minds of employees. Therefore the retaining of certain employees with critical or proprietary tacit

knowledge becomes a kind of holding cost which is paid through bonus salaries or other costly benefits. Additionally, as tacit knowledge resides in memory, it is subject to knowledge decay if left unused; and it suffers obsolescence if the field grows. Therefore, just as the organization must at times remove items from inventory, maintain and update them to keep them up to date, so it must also invoke methods to maintain and update its knowledge inventory. The cost of performing remedies, such as conducting drills or refresher training, to resolve this knowledge atrophy is another kind of holding cost.

Conversely, as employees know more, they may be able to develop novel solutions to difficult problems that they otherwise would not discover solely based on their prior knowledge [9, 14]. Therefore, it seems appropriate to consider that “holding” knowledge contains a *hidden benefit* derived from tacit knowledge stores that enable improved performance.

EOQ

For physical inventory, researchers have developed, and practitioners regularly use, Economic Order Quantity (EOQ) to determine the optimal amount of a physical good to order based on known demand, holding and set up costs. This method remains sound for many different *demand* approaches. For instance, Brill and Chaouch modeled *demand* using an exponential distribution in response to uncertain forecasts [6]. Interestingly, although some of the terms may be difficult to predict, the practitioner is comforted knowing that even a 25% error in EOQ results in only a 2.5 percent error in predicted inventory costs [39]. Therefore the method of EOQ is somewhat robust to input variability.

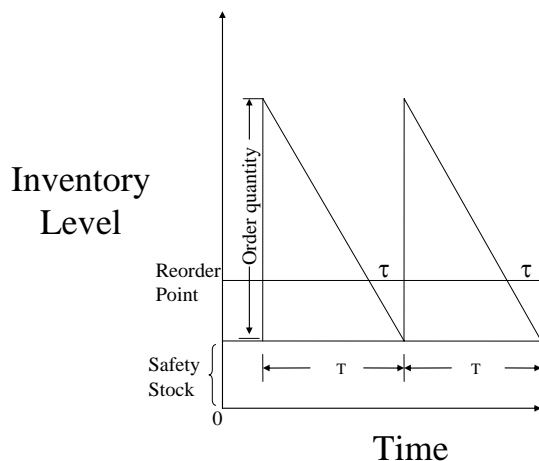


Figure 1: Inventory Model showing inventory levels over a cycle time (T), with lead time (τ), and order quantity (EOQ). The consistent and repeating reordering sequence shown allows for the maintenance of a static buffer or safety stock [39].

Figure 1 above illustrates the rise and fall of physical inventory levels given *known* demand, order lead time, and safety stock. The optimal amount ordered in this case would remain consistent and should be determined using the EOQ model. A short, qualitative example illustrates the use of EOQ with respect to *knowledge inventory*. First, let us consider that the organization requires a certain type of knowledge and can determine the relative magnitude of the input variables. For instance, this particular knowledge may exhibit relatively high knowledge subtractions (e.g., outflows resulting from decay and obsolescence), relatively low set-up costs (K), and relatively low holding costs (IC). It is seen that a near-optimal amount of knowledge inflow (i.e., knowledge to order) is high. Conversely, as knowledge subtractions remain relatively low due to a static environment, while keeping holding and setup costs equal, the optimal amount to order decreases.

Given the foregoing discussions concerning each of these costs, it seems that as the environment becomes more dynamic, a larger knowledge order (i.e., greater knowledge flow) is needed. Although a seemingly intuitive finding, this predictive model uses knowledge flow variable definitions that closely follow a proven method for determining optimal ordering of perishable physical goods, and produces similar outputs.

Inventory System Operating Costs

Aside from the costs associated with EOQ, the organization may consider the overhead requirements to keep track of its knowledge inventory. For instance, the operation of a physical inventory system includes the data collection system used to determine item demand and procurement lead-time and the cost of making decisions based on such data. This cost is generally static and presents only a small investment once market demand has been established. This remains true until major changes to operating doctrine are considered, such as changes to lead-time, reorder point, and safety stock. Assuming that the current re-supply doctrine is satisfactory, this cost is relatively predictable once demand for a particular item is known and remains predictable.

However, as demand becomes uncertain for both physical and knowledge inventory, obtaining the data required to determine knowledge demand can involve considerable human interaction. Specifically, accurate predictions of required knowledge inflows require clear insight into the future requirements of the organization and an accurate knowledge of what inventory the organization currently holds. Because there are multiple available methods to acquire knowledge with different lead times, this task becomes challenging to accomplish. Yet it is critical to perform it well to optimize the organization's use of scarce knowledge inflow resources. Conducting this kind of analysis can help managers to exploit available individual knowledge inflows optimally.

In a military setting for example, as a commander becomes more aware of the environment to be encountered and compares the knowledge demands of this environment to the available knowledge inventory and opportunity for knowledge inflows, s/he can achieve a more comprehensible understanding of unit readiness.

Operating Doctrines

Inventory operating doctrines provide the organization a framework to decide when, why, and how often reordering should be accomplished. Two inventory operating doctrines, Just-In-Time (JIT) and Just-In-Case (JIC), are well established in management science literature and in practice. An abbreviated description of each is provided.

Just-In-Time (JIT) began as a Japanese management philosophy chiefly to eliminate waste [39]. Its many beneficial results include reductions in physical inventory, thus saving holding costs and production as well as providing a more flexible organization capable of responding rapidly to changing customer demands. It also leverages the savings found through the use of EOQ ordering. JIT acts as a *pull* system [39, p. 351] using indications such as Kanban cards to trigger the next order. Ultimately, JIT seeks to provide resources, parts, and finished inventory *just in time*.

Just-In-Case (JIC) considers instead the value of slightly increased inventory levels in the event a part *may* be needed, seeking to avoid costly stock-out conditions. This extra inventory is indeed useful in uncertain environments with unknown demand. Therefore, while JIT seeks to minimize excess inventory in situations where demand can be accurately assessed, JIC considers the cost versus the potential worth of holding excess inventory in uncertain situations. To illustrate this, consider the recent New Orleans hurricane Katrina of 2005. The environmental change was unpredicted, and people holding surpluses of water and food benefited greatly from their extra inventory. In this case, the value of the JIC inventory far exceeded the cost to hold it.

With respect to knowledge inventory, each policy exhibits both desirable and undesirable traits. JIT seeks to accrue knowledge inflows just as they are needed, thereby saving time and money invested in holding knowledge that is unnecessary and reducing time available for knowledge outflows via decay and obsolescence. However, if the lead time for a certain type of knowledge is long or unpredictable, this may cause an unwanted *stock-out* condition which could be difficult and very expensive to remedy. However, if we implement JIT policies for short term, predictable lead time training to counter the effects of knowledge outflows due to decay, thus

providing critical knowledge for a project just as it is needed, this may serve the organization's knowledge inventory purposes well. This is true in the case of dynamic projects whose environments at the beginning may not be known or predictable – a circumstance that is common for today's military missions. Additionally, JIT could be used to represent how the organization distributes its specialist personnel to projects just as they are needed, thus avoiding the cost of educating too many to become specialists.

The JIC operating doctrine however provides for a "safety stock" [27] of many physical items to be maintained in the event of unexpected demand. Therefore, with respect to knowledge inventory, an organization may wish to retain some employees with graduate level education in the event that their broad and deep knowledge might become beneficial. Although this policy causes the organization to hold knowledge that may never be used, it provides flexibility for an organization to respond quickly to unforeseen circumstances. Alternatively, implementing a JIC policy organization-wide, whereby all employees are formally and generally educated, would be a very costly proposition. However, there is reason to suspect that at least some of the employees should be generally educated in the event that unforeseen circumstances require their knowledge. Additionally, as more knowledge is held, more knowledge is available for potential diffusion. Therefore, the organization must balance the usefulness of holding many kinds of knowledge versus the caustic effects of decay and obsolescence.

Both doctrines are useful at times and must be weighed carefully by the organization. Because of their inherent decentralization, Edge organizations place a high premium on appropriate knowledge distribution and sharing and are highly sensitive to stock-outs of required knowledge. We, therefore, argue that a combination of JIT and JIC should be considered by the organization to provide near-optimal inventory policies. We postulate that a JIT policy should be followed when the environment is static and can be predicted. However, to the extent that the environment is dynamic and cannot be predicted, the organization should leverage the cost savings of JIT with the supportive policies of JIC. For instance, many scholars argue that both *specialist* and *generalist* knowledge are required to enable organizational success [47]. As predictable but difficult issues are encountered by the organization, the specialist is needed. However, if the circumstance has never been encountered, the specialist may be unable to solve the issue, whereas the generalist may be able to abstract from similar knowledge to determine the best method to resolve the issue.

Issues with the Analogy of Knowledge Inventory as Perishable Goods

Although insightful theoretically, using this metaphor *perishable goods inventory* to conceptualize the dynamics of knowledge stocks and flows in the organization suffers from two limitations. First, when knowledge is "demanded" in an inventory sense, it can actually increase due to its diffusion among workers. In fact, the more it is used, the more it tends to grow! Cohen & Levinthal (1990) [14, p.129], state that "as more objects, patterns, and concepts are stored in memory, the more readily is new information about these constructs acquired and the more facile is the individual in using them in new settings." Therefore we refrain from using the term "knowledge demand" but instead refer to "knowledge inventory subtractions" or "outflows" to refer to losses mentioned above such as employee turnover, knowledge decay, interference, and obsolescence.

Second, knowledge can be used by many people yet not be depleted, making *knowledge inventory* difficult to quantify. Thus, certain kinds of (esp. explicit) knowledge also exhibit the trait of a *public, collective or nonrivalrous good* [24] and exhibit the quality of *jointness of supply* [38]. Alternatively, other kinds of (esp. tacit) knowledge cannot be shared at all. This difference is best resolved considering the bounds of the organization [24]. For instance, if an individual belonging to an organization shares knowledge within the organization (or partner organizations), the organization has not lost its competitive advantage gained by his expertise. Indeed, such advantage would likely increase as the shared knowledge expands its reach through the organization. Yet if he shares this knowledge outside the organization, a potentially damaging loss has occurred. This loss could be prevented or at least made illegal through the use of non-disclosure statements, patents, and copyrights. Ultimately, we seek the diffusion of knowledge within the firm and consider knowledge inventory as the holdings of the firm and its employees.

Phase II

Current research refines the theoretical framework to describe, model and simulate knowledge flows in Edge organizations by computationally modeling the dynamic phenomenon of skill acquisition and decay for individuals.

We concede that illustrating, managing, and quantifying knowledge is challenging. Knowledge considered as a collective set of skills held by organizations must first be characterized and classified amongst its individual members. Cohen and Levinthal argue that “An organization’s absorptive capacity depend on the *absorptive capacities* of its individual members” [14]. We therefore seek to improve our understanding of how to model individual skill acquisition and decay and inform practitioners why each occurs. Specifically, during Phase II we seek to understand:

- How individual skill acquisition and decay can be computationally modeled, calibrated, and validated and,
- How Edge organizations and projects are effected by the sum of individual participants’ skill growth and decay.

In order to measure knowledge level quantitatively, we seek to measure knowledge via the performance of *skill*. Skill accounts for both tacit and explicit knowledge, and by leveraging well-substantiated learning and forgetting curves, converts knowledge into a form capable of being quantitatively measured – via the *speed of processing*, and perhaps also via *error rates*.

This exploratory effort draws from the literatures of cognitive psychology (e.g. [18, 21, 23, 29, 48, 49, 61]), organizational simulation [30, 32, 33] and organizational knowledge and power (e.g. [16, 17, 20, 22, 44]). We have begun to aggregate and synthesize findings from research that further discusses skill acquisition and decay [7, 8, 13]. This effort seeks to build upon the knowledge inventory framework discussed above and refines and informs individual knowledge growth and decay. As a necessary first step, we begin by considering the different means and contexts by which others have modeled knowledge inflows and outflows through the use of learning and forgetting curves. We instantiate and categorize learning and forgetting curves [21] based on well substantiated, empirically based, learning and forgetting curves (e.g. [2, 52, 61]) and the latest developments of learning classifications using skill categorization, whereby skills and their concomitant learning curves are placed in categories (e.g., learning or forgetting of motor vs. cognitive skills) based on their context [18, 28, 52].

One limitation of organizational learning curves is that they are highly aggregated and can lack the level of granularity available through the analysis of individual agents. We seek to overcome this limitation and inform organizational learning by imbuing agents with skills necessary to accomplish assigned tasks within an organization. We also allow these skills to increase and decrease dynamically as knowledge interventions cause inflows and outflows. This refinement allows us to analyze the effectiveness of different knowledge flow management approaches computationally by using a set of extensions to the *Virtual Design Team* (VDT) Monte Carlo, discrete event organization simulation [30, 32, 33].

New software entitled POW-ER (Process, Organization, Work for Edge Research) is used and initial learning parameters are embedded in POW-ER *agents* based on micro-behaviors found through a review of social and cognitive psychology literature on learning and forgetting. We test our representation and reasoning of knowledge flows by executing synthetic *gedanken* or thought experiments for initial validation, followed by a series of simulations that further serve to validate, calibrate and refine the POW-ER parameters [57]. Finally we seek further refinement as well as validation through ethnographic, empirical studies held within the context of shipboard operations to be conducted in June 2006. Through POW-ER, we expect to predict the impacts of alternative knowledge flow interventions (such as formal training, on-the-job training, and mentoring) as well as the effects of knowledge decay (due to time, interference, employee turnover, and obsolescence) on the effectiveness of Edge and other military organizations for different skill and environmental contexts.

VDT is project-focused and thus models individual knowledge levels in its organization simulations as static for each individual (low, medium, and high) for the duration of a single project. We use POW-ER to model and simulate knowledge as a continuous and dynamic

variable and attempt to develop new understanding about how to facilitate, enhance and measure knowledge flows and organizational power.

Our computational experiments are designed to (1) begin validating and calibrating the knowledge flow parameters and algorithms in POW-ER; and (2) develop some initial insights about promising organizational interventions to optimize the design of Edge organizations with respect to future elaboration and validation of knowledge and power flows. In his paper to the 10th ICCRTS conference, Nissen examines computational models using a theoretically defined Edge organization [39]. We build upon this work, using many of the same definitions and modeling techniques as we continue forward with our line of research.

This next section provides background into what is known in the social and cognitive psychology literature about skill acquisition and decay. We begin by reviewing individual cognitive learning and forgetting, followed by our exploration of different knowledge interventions. We close this section with a discussion of field growth and skill classification.

Learning and Forgetting Theory

There is much to consider in how people learn. We would be naïve to consider that we might answer the modeling concerns about all that there is to know about how humans learn and forget. For instance studies show that experts differ from novices in how they learn, specifically that they look for patterns that can more easily be recalled and used for future advantage, in a chess game for example [8]. Organization of knowledge or *chunking* [37] has also been posited as a means by which more experienced knowledge workers are able to store increasing amounts of information. It is also interesting to note how experts approach problems in terms of available responses considered first and, through the use of flexible heuristics, finally reach a solution [9]. It is also argued that experts and talent are not innately granted their abilities, but achieve the level of virtuoso or recognized expert through *deliberate practice* [23] over many years.

Each of these and many other thoughts about how learning takes place are intriguing, but very difficult to model, given the individuality of each participant and the timing of individual strategies as they are employed. We instead use models that have been replicated via repeated empirical experimentation [e.g. 4, 19] as a point of departure and extend them toward modeling skill acquisition and decay. The following figure illustrates for instance the Power Law of Learning [45] derived from empirical studies that appears ubiquitously in cognitive psychology texts (e.g. [2]).

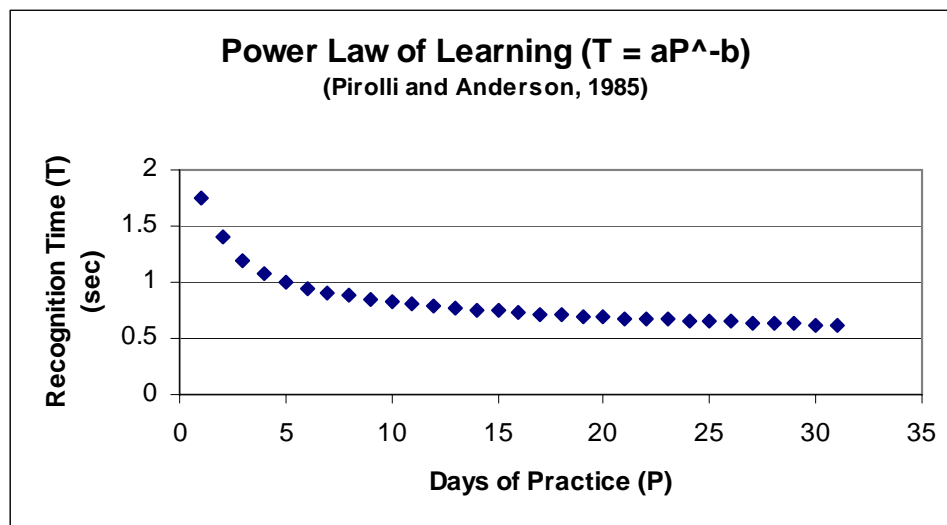


Figure 2: Power Law of Learning. Over increasing days of practice, a simple recognition task (time required to recognize sentences) requires ever decreasing amounts of time [as found in 2].

For virtually all learned skills, we observe that a skill may require many hours to perform at first, whereas on the second and third attempt, less and less time is required to perform the same skill with the same outcome. It is also observed that no matter how much the participant practices, most skills never improve past a certain, required amount of time as Figure 2 illustrates.

There are three knowledge interventions we model that serve to increase individual knowledge. They are: (1) mentoring which requires the time of an expert who closely observes and teaches the worker, (2) formal training which occurs in a focused form to improve skill and in short duration, and (3) On-the-Job Training (OJT) which arises from performing the skill. Additionally, there are four that serve to decrease knowledge they are: (1) decay from lack of usage, (2) interference, (3) employee turnover, and (4) obsolescence.

While each knowledge intervention serves to alter knowledge inventory, observed through the lens of skill acquisition and decay, they do so at different rates and with different characteristics. Table 2 provides a summary of these characteristics with a more detailed discussion in the section that follows.

Table 2. Knowledge Intervention Characteristics

Skill Effect	Knowledge Intervention	Characteristics
Growth	Mentoring	Fast transfer of knowledge, yet has limited reach and requires expert's time
Growth	Formal training	Medium transfer of knowledge with improved reach among employees and removes employees from production
Growth	On-The-Job Training	Slow transfer of knowledge, yet production is uninterrupted
Decay	Decay from time	Variable for different skills
Decay	Interference	Caused by competing tasks
Decay	Employee Turnover	Complete loss of individual's knowledge
Decay	Obsolescence	Caused by a growing field of knowledge

With respect to skill growth, mentoring provides quick and personalized feedback on errors as well as tailored training, thus enabling faster learning at the individual and potentially group levels [2]. It also has beneficial effects in both tacit and explicit knowledge dimensions based on assiduous mentor contact, and because the level of knowledge being transferred is likely highly evolved in terms of *life cycle* [41] or maturity. However, mentoring is costly; and assumes that more knowledgeable employees are available and that the organization can function temporarily without them. Mentoring in this instance refers only to that process by which individual transfer of expert knowledge is conducted and does not include other forms such as career planning or counseling.

Alternatively, employees may be formally trained, where unlike learning on the job (OJT); a worker must stop performing his job and attend a temporary yet helpful educational session where we can expect his skill to improve moderately. An example of this might be short weekly lectures or practical demonstrations. While not as expansive in terms of amount and type of knowledge transferred, it provides a low cost solution toward increasing knowledge in the short term and provides reasonably strong benefits to the individual and organization.

Finally, as a project continues, each employee simply learns on the job (OJT), which involves relatively slow transfers of perfunctory knowledge at the individual level and which may result in many errors along the way.

Decreases in skill arise from a lack of usage, *interference* due to other tasks, and from obsolescence. Employee turnover also causes all individually held knowledge of that employee

to be lost to the organization. We therefore deem these as appropriate means by which employees decrease their knowledge within an organization.

Knowledge decay at the individual level—and arguably also at the group and organization levels—occurs on a much slower scale and is caused by two phenomena – time and interference [2].

Directly stated, time delay causes employees to forget. The rate at which forgetting occurs increases with task complexity and with simple failure to recall an item or procedure with some frequency [28]. To understand forgetting, we first turn to the earliest writings and findings of Ebbinghaus [21] who posited that forgetting functions occur in a logarithmic form. Alternatively, Wickelgren [60] argued that forgetting functions occur and are better described using a *power law* such as: $R(t) = at^{-b}$ where t is time and a and b are scalars. Proven through myriad empirical examples, most researchers [61] concur that individual forgetting can be modeled via the power law, as shown in Figure 3 below.

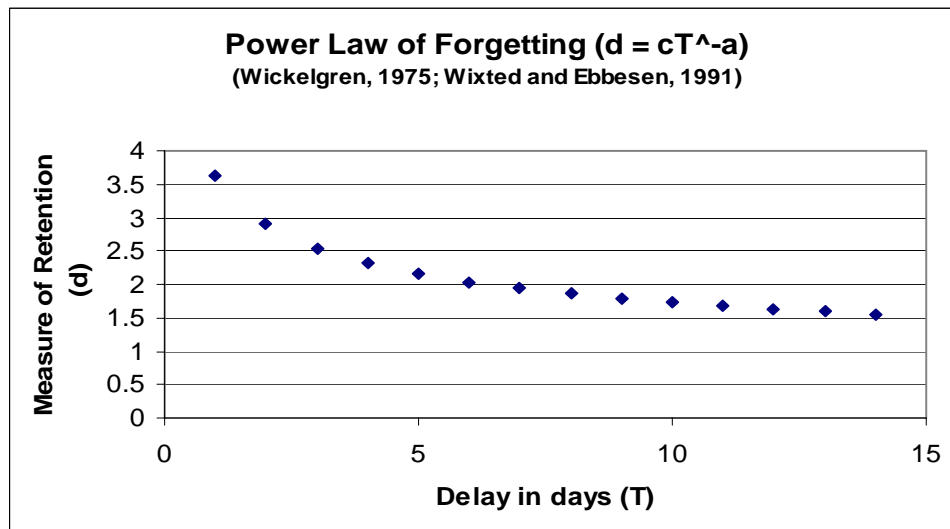


Figure 3: Power Law of Forgetting. Over time what is known decays at a negatively accelerated pace.

These examples and many like them captured in cognitive psychology literature (e.g. [2]) exhibit the phenomenon of *list learning* where a participant is asked to recollect and recite memorized items from a list and over time, begins to forget them. This same effect is seen, yet more difficult to control, in the recall and performance of complex *skills*. It is our position that skills follow this same pattern of growth and decay as shown through the study by Smith [54] with regard to the knowledge *half-life* for a physician as well as McKenna’s inquiry of *decay* in cardiopulmonary resuscitation (CPR) skills [34].

Coupled with forgetting is the phenomenon of *interference*. Interference [3] considers the number of other tasks that have been accomplished between target events of interest, bumping out portions of the original knowledge [2] or by selecting portions of knowledge viewed by the user to be more useful in the current context [3]. Although decay results in reduced skill levels, it can be remedied through frequent (re)training [29].

Individuals may fail to *practice* a given skill for a relatively long period of time; however, in many domains, just a small amount of practice is sufficient to quickly return knowledge to the level reached before [2]. Moreover, in cases of experimental cognitive remembering, once an item has been recalled, it tends to remain neurologically available for some amount of time thereafter [58].

We have recently begun to develop a new software (POW-ER) that takes as input the skill level of an agent and allows that level to change dynamically based on performing (or not

performing) the skill. It also allows us to decrease skill level based upon *interference* from a competing task. Thus far, the *microbehaviors* of individual skill growth and decay are implemented in POW-ER and appear to be working qualitatively correctly, but are not yet fully calibrated or validated. Figure 7 below graphs the output result from a simulation of one agent using one skill. OJT knowledge flow initially causes the skill level (measured as Agent Processing Speed on the vertical axis) to rise. In turn, the agent begins to enhance its second skill and neglects the first, causing the first skill to decrease in *processing speed* and allowing the second to increase. In this proof of concept case, the agent begins at a skill level of medium (Agent Processing Speed = 1.0) and at times rises to a level of 1.4 as a result of practice in using the skill. Each agent's *processing speed* has far reaching implications throughout the organizational simulation that will directly affect expected project cost, length, rework and project risk. Agent exception probabilities change with changes in skill levels in the opposite direction from changes in processing speed, thus further amplifying the effects of knowledge flows on organizational performance.

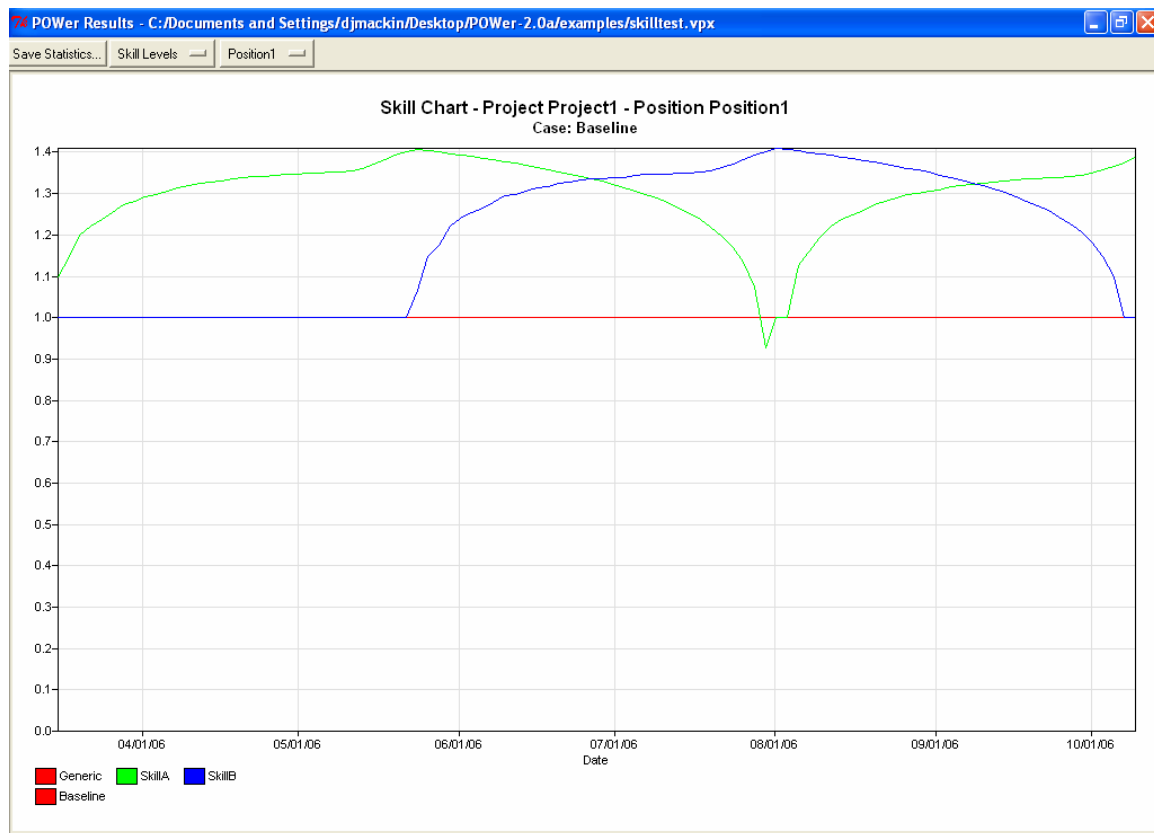


Figure 7: Dynamic agent increase and decrease in two skills as a result of learning by doing followed by forgetting as well as interference between the two skills. The horizontal axis models repetition of tasks over time; the vertical axis shows Agent Processing Speed, where a value of 1.0 corresponds to an agent with a “Medium” skill level for a given task.

Obsolescence

Within this Phase II effort to model skill acquisition and decay, the notion arises that although skills may be caused to increase via many knowledge interventions, it may also be the case that *knowledge obsolescence* can occur due to the volatility or dynamism of an uncertain environment [12], thus causing what is currently *known* to be increasingly less useful. For example, knowledge of plumbing may remain current for some time because it is slowly changing

field, whereas knowledge of software engineering may only remain current for a year or two due to a more dynamic technology and market environment. And knowledge available about how to locate and avoid enemy anti-aircraft sites may need be revised daily. Therefore, to maintain a skill such as avoiding anti-aircraft sites may require much more frequent training. Obsolescence affects all levels of knowledge *reach* (individual, group, organization and intra-organization) [41].

To operationalize this idea we begin by considering a percent of knowledge held by each individual with respect to the field. Therefore, we must define numerator and a denominator. The numerator is the amount of knowledge held by the individual in a certain field of expertise and is noted as (k). The denominator is the amount of knowledge in the total field and is noted as (K). We consider a beginner's percent of knowledge to be relatively low (e.g. 10%), and conversely, an expert's percent of knowledge to be relatively high (e.g. 90%). We next consider how each of these variables k and K may change. The rate of change of individually held knowledge (k) is managed by the knowledge additions and subtractions discussed earlier. For instance, k would increase given the type of knowledge intervention, amount and recency of learning accomplished; however it would decrease due to knowledge decay caused by elapsed time and interference. Field-wide knowledge (K) would also change. As the environment becomes dynamic, more knowledge is created thus proportionally increasing K . This manifests the type of skill improvement to be pursued in uncertain environments. This idea also invokes a theory of *continuous improvement*, where firms "unceasingly strive to improve performance" [63, p.919]. Figure 4 below illustrates this idea.

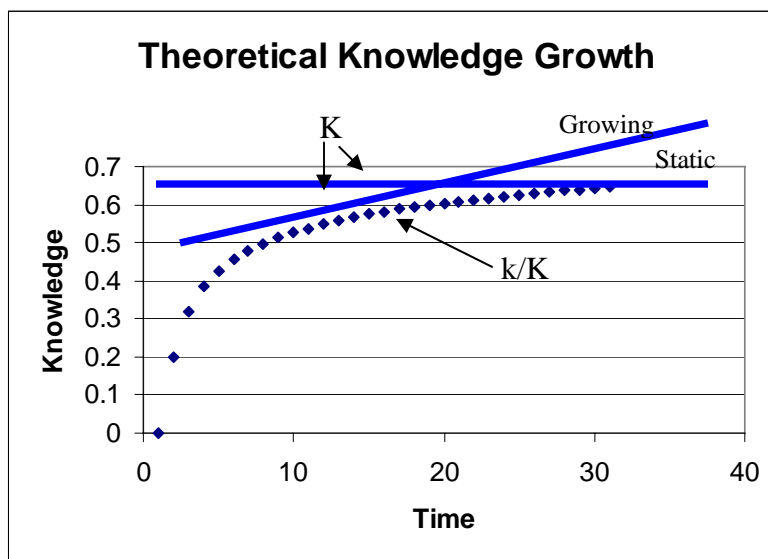


Figure 4: Knowledge Growth. We consider that as time continues and the knowledge in a field (K) increases, more individual skill (k) must be achieved just to maintain current k/K knowledge levels. Therefore, levels of required skill may either be *static* or *growing*.

Some research has been published on the rate of obsolescence of technical knowledge [51] in which a rate change for patent applications was used as a surrogate means to detect field obsolescence or growth. Our inquiry is limited to theoretical extensions of skill obsolescence that may indicate the frequency and depth of re-training required to keep pace with the evolution of knowledge in a given field. As we observe a knowledge level increasing with days of practice [23], we anticipate movement along the existing knowledge metric curve, illustrating how an individual would progress toward 100% (k/K) as time and learning continues. Figure 4, contains an anticipated curve that would result from the calculated knowledge metric, where formula coefficients are approximated at present for illustrative purposes. This illustration offers a useful, yet somewhat theoretical tool for demonstrating how an individual's knowledge may or may not be sufficient toward achieving and/or maintaining a certain knowledge level in a growing field.

To move forward, we need a calibrated and validated computational model of the effects of alternative knowledge flow interventions on individual performance and hence on organizational performance of teams. Building such a model is the goal of the current phase of the research. Conceptually, we do not attempt to quantify knowledge as a metric, but instead measure processing speed as a surrogate measure of knowledge held. And, as mentioned in the obsolescence section above, we also consider knowledge as a percent of what can be known in a specific field of expertise. By considering both individual knowledge (k) and field-wide knowledge (K), the organization has a metric of more than just how much knowledge its employees possess, but how that knowledge amount compares to the total knowledge available and required for successful performance.

Considering the behavior of individual knowledge (k), we first observe an opportunity to view an aggregate and intriguing method of illustrating organizational knowledge. By using percent knowledge metric (k/K), we can conceive how organizational knowledge flow modeling may be improved. From this we postulate that close approximations to k and K that allow us to determine individual as well as organizational knowledge. Taken one step further this enables a promising heuristic for studying organizational learning as well.

Skill Classification

Certainly not all skills are learned with equal speed. Dar-EI et al. [18] provide an interesting finding in their classification of skills in the four following categories: (1) highly cognitive, (2) more cognitive than motor, (3) More motor than cognitive, and (4) highly motor. Their finding was also tested against earlier data taken by other experiments and shown to be predictive of the learning curve shape for that particular type of skill. We build on this theory by providing a skill classification to improve the prediction of the learning curve shape, and thereby improve the prediction of skill levels over time. Figure 5 below illustrates their findings.

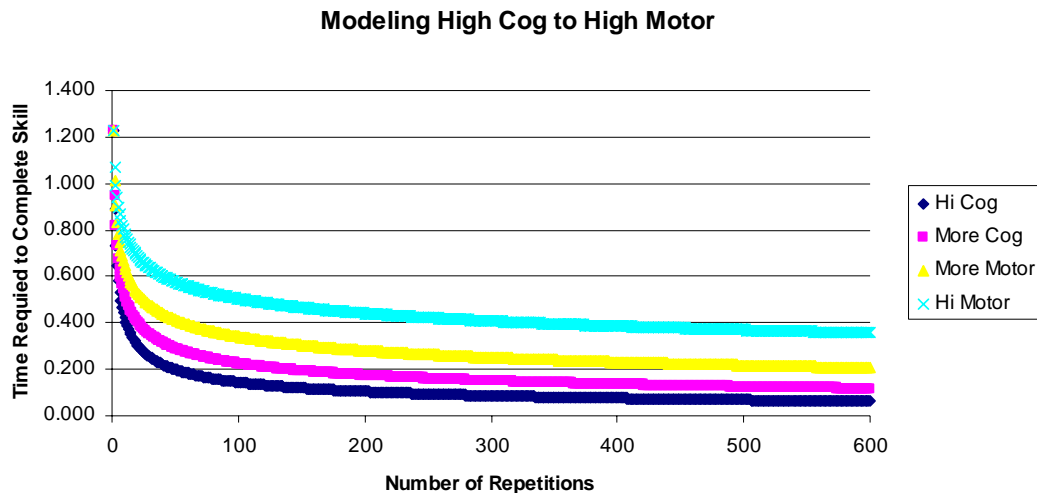


Figure 5: Learning Curves for different types of skill (replicated from Dar-EI et al., 1995). As skills become increasingly motor rather than cognitive, they tend to be learned quicker [18].

In closing this background section and further motivating our research, let us consider the necessary planning to achieve project (or mission) success in terms of worker knowledge. Specifically, most decision makers have at their disposal the ability to determine present worker education and training levels in considering needs and requirements toward accomplishing a new project. This static representation of a list of skill-sets, though seemingly complete, fails to inform the decision maker about how to interpret future knowledge requirements. Nor does this kind of static skills model provide a means to consider the volatility of the knowledge currently held by

workers, or an alternative means whereby resources may be most effectively used to add to current knowledge.

Integration of Phases I and II

Here we discuss how Phases I and II are brought together to inform organizational level experimentation. A short discussion beginning with cost analysis provides the basis of the discussion and comparisons among different knowledge interventions. This comparison leads logically then to selection of near-optimized knowledge and power flows. We also include a revised graph of *knowledge inventory* using what we have learned from cognitive skill acquisition and decay. We close this section by outlining our planned experiments - the findings of which are to be included and analyzed in the final draft of this paper.

Costs

Through experimentation using our model, we show costs of skill acquisition and decay through resulting project length and levels of exception handling. For instance, if an organization suffers from decreased levels of skill it will likely perform assigned projects more slowly and with more errors. Conversely if skill is maintained at high levels via constant mentoring and training, workers spend less time working. And, as mentioned above, skill levels also affect the quality and safety of task outcomes. Thus, each situation has a different optimal set of knowledge flow interventions that are the most advantageous in terms of duration to complete the task, total cost, and quality of outcomes. Table 3 pairs knowledge interventions with their putative organizational costs and benefits.

Table 3. Knowledge intervention costs

Knowledge Intervention	Costs	Benefits
Mentoring	Lost time of expert for the duration of mentoring, incomplete or "filtered" mentor tacit knowledge converted into explicit knowledge	Fastest means of personalized, tacit, mentor knowledge inflow to worker plus productive work still continues (by the worker)
Formal training	Trainer salary plus the temporary loss of worker	Wider reach of knowledge transfer to many individuals, relatively low cost
On-The-Job training	Relatively slow knowledge flow occurs; less capable worker than if trained and/or mentored	Minimal cost
Time delay of skill	Loss of skill over time	Allows opportunity for other skills to be performed
Interference	Rapid loss of skill over time	May provide a method for workers to purposefully forget inferior practices
Environmental changes	Requires skill growth to maintain current performance level	Provides potential advantage if skills are already available among workers

From Table 3, each knowledge intervention has a unique set of relative costs and benefits. Therefore, there exists a delicate balance between costs and benefits in determining the appropriate mix of knowledge flow interventions for a given situation. Different combinations of knowledge inflows are highly situation-specific, and depend on the nature of work, the existing skill levels of workers and expert mentors, and the opportunity costs for mentors' time away from other tasks, leading to potential for delay and quality failures. Through organizational simulation we seek to determine the contingently optimal combination and level of skill acquisition that should be pursued in order to reap the benefits, and overcome the costs, of knowledge inflows.

For instance on a short project, there is not time enough for workers to all attend training; on a longer project, there may be both the need for workers to be trained and enough time for the organization to benefit from the costs invested toward improved knowledge inventory. Just as the organization considers overall project cost, it must also consider how often and at what level it must require inflows of knowledge to occur to maintain a level of proficiency required to be successful in a given environment.

This next section considers how learning and forgetting rates inform our knowledge inventory framework.

Applying Knowledge Inventory Curves to Command and Control

Alberts and Hayes state that *command* is that which is “involved in setting initial conditions and providing overall intent.” *Control* is separate from command: “an emergent property that is a function of the initial conditions, the environment, and the adversaries” [1, p. 217] (emphasis mine). Using our findings from research efforts thus far, we consider an example that seeks to enhance *initial conditions* through informing the Commander of knowledge inventory holdings.

Starting with the inventory illustration shown above in Figure 1, we develop a revised illustration of how a military organization’s knowledge inventory might appear using cognitive, learning and forgetting curves as a guide. We also combine the aspects of a how a field of knowledge that is growing due to environmental uncertainty might affect the original graph in Figure 6 below.

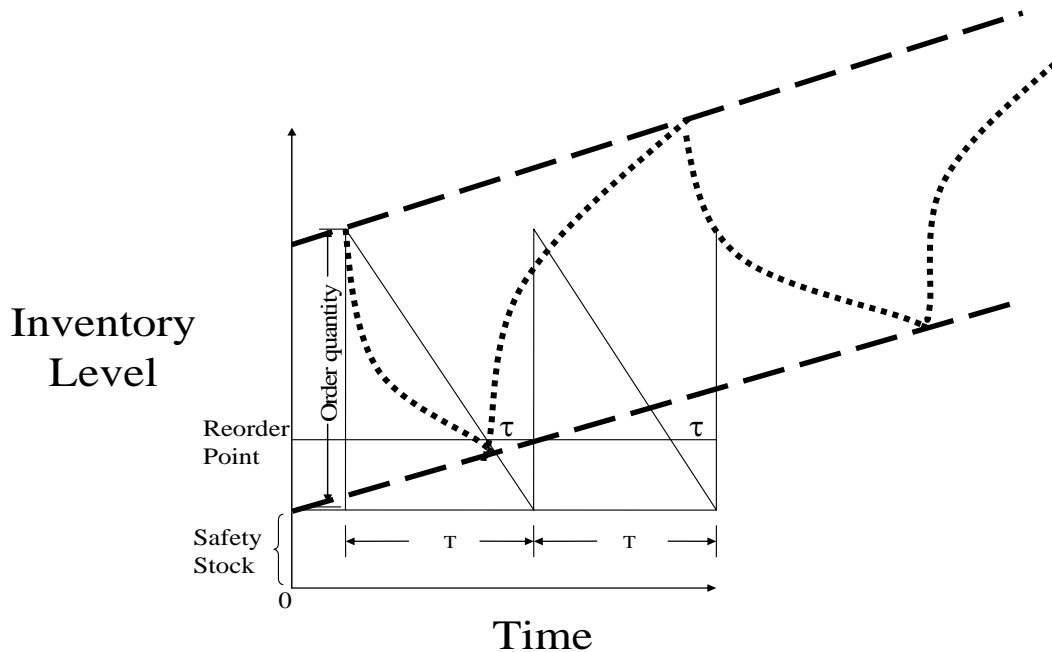


Figure 6: Knowledge Inventory Model showing learning and forgetting rates (dotted lines) that occur within a framework of a growing field of available knowledge.

From this illustration we note that knowledge decays quickly at first, then decreases at a decreasing rate. This is followed by a re-supply period of fast knowledge growth that also occurs quickly at first yet increases at a decreasing rate afterwards. The entire slope however is caused to rise, as illustrated in Figure 6 above, due to the increasing level of knowledge in a growing field of available knowledge – and the desire to maintain an adequate knowledge inventory to cope with this changing environment. Observe in Figure 6 that, unlike for physical goods – even perishable ones - instantaneous re-supply does not occur. In the case of knowledge inflow, we

observe that a longer amount of time is required to build inventory which may explain why it may be risky to allow reduced levels of proficiency to develop. Also note that knowledge outflows occur relatively quickly. We must consider the means and lead times of inflows available to us to remedy the knowledge outflow in a timely manner. For instance mentoring may provide the fastest means to provide knowledge inflow, but incurs a high cost of experts' time. Formal training may be employed and is relatively inexpensive, but is somewhat slower. In contrast, on-the-job training is a slow but very inexpensive form of knowledge inflow that allows productive work to continue. We might also consider the slope at which knowledge outflow occurs with regard to knowledge decay, interference and obsolescence. If we observe relatively slow decay, on-the-job-training may be a sufficient form of inflow to maintain the requisite knowledge level. If, however, the observed skill is highly complex and therefore subject to rapid decay, we may need to provide mentoring and frequent formal training to maintain proficiency. We may also identify that some workers are simply overburdened and suffer from too much interference. In this case, organizational design and task assignments may be altered to avoid the knowledge outflow caused from excessive interference.

Note also that the safety stock must rise to keep pace with the growing field of knowledge; and shorter cycle times (T) must be maintained through more frequent skill performance or training to maintain required higher levels of knowledge inventory. From the obsolescence discussion in the previous section, we observe that increases in field-wide knowledge (K), for instance, would cause longer amounts of time to transition upward in Figure 6.

These ideas are illustrated and analyzed via a current, command and control example. There are myriad different required skills for a strike group operating at sea - each with varying levels of growth and decay that should be managed – a difficult and nearly insurmountable problem to manage. If however, each unit commander or Captain were to analyze his own ship's personnel knowledge inventory using the framework of knowledge flows and cognitive methods outlined above, he or she would be able to prioritize which knowledge inflows might be needed and when. The Captain would also benefit from consideration of the constant inflows and outflows associated with each required type of skill. Interestingly, required skills are assigned by hull type and delineated in Navy publications and are available to each Commanding Officer. Prior to sailing, each Captain might therefore create a tailored plan for his ship given the personnel knowledge inventories and his resources to affect knowledge inflows via mentoring, formal training, and on-the-job training. The lead time for each of these knowledge outflows would also be important when considering which inflow might be implemented to resolve them.

For instance, just before the ship gets underway, mentoring might be used with new crew members to develop urgently needed skills such as ship driving and navigation until a high level of proficiency is reached. As an alternate instance, while the ship has considerable time before its scheduled departure, mentoring may give way to or be augmented by formal training. Further, less frequently used and less critical skills may be learned via formal training at first, while the ship remains pierside, followed then by periods of on-the-job-training as appropriate, to maintain proficiency as the ship's underway date nears.

As part of this planning, the Captain might also consider knowledge outflows caused by personnel turnover, knowledge decay, interference, and obsolescence. The identification of turnover dates of experts and the identification of their prospective *reliefs* would be a first step toward overcoming knowledge outflows from employee turnover. The second step would be to ensure that the prospective experts receive the knowledge inflows they need to become as proficient as an expert. It seems a high percentage of mentoring combined with a decreased percentage of formal training with on-the-job training would be in order here. With regard to all other skills, knowledge decay rates from more complex tasks, measured against the likelihood of their use would be informed from this analysis process. Organizational design might also be altered to allow for reduced interference by reducing the number of skills required by each worker. Obsolescence would also be considered in determining which mission areas are subject to growth from uncertain environmental effects such as new tactics in controlling and coalescing available data from Unmanned Air Vehicles (UAV's). This process would cause the commander to require increased time learning and practicing in these areas and to spend less time on the more static areas where knowledge is not subject to growth or environmental uncertainty.

As a result of this effort, the Captain would be informed of the weaknesses in readiness in certain mission areas prior to the performance or assignment of his mission. This sort of analysis would also enable the Captain to consider the type and usefulness of his organizational design. Even today's military is granted some autonomy to decide how to configure its own chain of command (organization design).

These inventories, accompanied by their prioritized requirements for knowledge inflows, once aggregated, might also inform the Strike Group Commander as to the readiness of the Group in each mission area and where to spend time training. And if this knowledge inventory were shared throughout the Strike Group, ships could communicate among themselves in an edge-like fashion to enable improved training and honest sharing of strengths and weaknesses, thus supporting the ideals of *self-synchronization* and *shared-awareness* [1]. If this effort is accomplished early enough in the training cycle prior to deployment and the Commander is informed of potential strengths and weaknesses with regard to future skill levels, s/he can make improved use of critical and limited resources – personnel, time and money. Thus through these efforts, *initial conditions* may not only be known, they may be controlled and improved.

Experimentation: Present and Future

We have begun work to combine Phase I (inventory control) and Phase II (skill acquisition), and have conducted our first set of intellectual (or idealized) experiments. In this exploratory effort we simulate one Edge organization and one Hierarchy organization, each with the same volume of work observed in executing joint command missions using surface, air and ground forces. Command functions are added only to the traditional Hierarchy organization. Our models attempt to follow the organizational framework and work processes implemented by Nissen [42]. Our results for the comparable scenarios are qualitatively similar to Nissen's but diverge in certain details, since they are implemented in a different simulation tool (POW-ER V1.1.6).

We next describe our modeling efforts to experiment with different lengths of training that result in increased skill levels for the trained agents. We use as our baselines and source of control, models of both an edge and a Hierarchy organization without training, shown in the first column of each table. We then add training tasks that improve agents' skill levels, but incur a fixed amount of time and cost to accomplish. For instance, we add 0.5 days of training that each agent must attend which results in agent skill level increasing from *low* to *medium*. In a third run, we require 2.5 days of training for each agent, which results in skill changing from *low* to *high*. Our preliminary findings are listed in Tables 4 and 5 below.

Table 4. Preliminary Experimental Results for Hierarchy Organization modeled in the 21st Century with training that lasts .5 days and 2.5 days. (The number beside each datum is standard deviation and the number below each datum is the percent of baseline.)

Measure	Hierarchy Organization: 21 st Century (baseline)	.5 Days of Training (skill goes from low to medium)	2.5 Days of Training (skill goes from low to high)
Duration	447 days (364)	332 days (448)	314 days (564)
	-	(74%)	(70%)
Cost	\$149M (28M)	\$114M (26M)	\$94M (23M)
	-	(77%)	(63%)
Project Risk	.756 (.196)	.757 (.194)	.760 (.226)
	-	(100%)	(100%)
Work Volume	77K days (0)	83K days (0)	110K days (0)
	-	(109%)	(143%)
Rework Volume	10K days (6K)	17K days (10K)	20K days (14K)
	-	(163%)	(191%)

Table 5. Preliminary Experimental Results for Edge Organization modeled in the 21st Century with training that lasts .5 days and 2.5 days. (The number beside each datum is standard deviation and the number below each datum is the percent of baseline.)

Measure	Edge Organization: 21 st Century (baseline)	.5 Days of Training (skill goes from low to medium)	2.5 Days of Training (skill goes from low to high)
Duration	45 days (2)	37 days (3)	30 days (3)
	-	(82%)	(68%)
Cost	\$123M (3M)	\$97M (4M)	\$79M (4M)
	-	(79%)	(65%)
Project Risk	.780 (.148)	.780 (.152)	.751 (.200)
	-	(100%)	(96%)
Work Volume	75K days (0)	82K days (0)	107K days (0)
	-	(108%)	(142%)
Rework Volume	6K days (2K)	13K days (4K)	15K days (5K)
	-	(209%)	(246%)

The terms *duration* and *cost* refer to the length of time and the total cost required for performance of a mission. *Project risk* measures mission-level rework tasks left incomplete at the end of a mission. *Work volume* indicates the total amount of work accomplished by the end of the mission by all agents, whereas *rework volume* indicates the amount of work that had to be spent to fix mistakes.

From these preliminary results, we note that for each organization type, as skill increases as a result of training, mission *duration* and *cost* decrease while *work volume* and *rework volume* increase when compared to each simulation's baseline. It seems likely that project duration should decrease as an agent's skill rises. This reduction in duration results in reduced overall cost, yet provides an increase in work volume because as agent skill increases, work volume increases, driven by the response to rework which seeks to be completed, rather than being ignored. Rework volume, as a fraction of the total work volume, seems to remain constant at approximately 1% to 2% over the duration of each mission. As agents become more skilled, their processing speed also increases, making them more productive and able to accomplish more work in less time. Since cost is based on agent salary multiplied by working duration, and we make the assumption that salaries remain the same a skill changes, costs decrease with increased skill. Another source of increased work volume is training time required for every agent.

Note that, consistent with Nissen (2005) [42], the Edge organization provides a much better fit for the 21st century mission environment than the Hierarchy does, with the key performance measure mission duration reflecting an order of magnitude greater speed. Given the importance of speed in warfare, this represents a very noteworthy finding. We expect to continue and refine these preliminary findings as our work toward understanding the effects of agent skill continues.

Over the next three months we will carry out additional intellectual experiments as well as conduct emulation (empirical) experiments to refine and validate our learning and forgetting model with the goal of determining organizationally, contingently optimal knowledge intervention strategies. More specifically, once we have validated individual micro-behaviors, we will perform organizational level computational experiments within different contexts and different organizational designs to explore and overlay the costs and benefits of OJT, formal training, and mentoring, combined with knowledge decays of time delay, interference, and obsolescence. Each of these factors will be varied separately, then combined in pairs, then modeled with multiple interventions acting simultaneously to achieve a *full-factorial* design.

Our experiments will be designed to explore:

1. Evolution of trans-specialist knowledge [47], which is modeled as knowledge of other specialists objectives and constraints, and should therefore enable decreased work stoppages (exceptions) due to lack of knowledge related to task interdependencies and, consequently, to reduced rework.

2. Minimum levels of knowledge adequate to commence a project within a fixed amount of time; and optimal intervention strategies to shorten project time.
3. The cost of maintaining knowledge levels too high as a result of constant mentoring and training.
4. The effects of knowledge stock-outs, to determine the organizational knowledge levels beyond which recovery may exceed available resources. Because of their inherent decentralization, Edge organizations place a high premium on appropriate knowledge distribution and sharing and are highly sensitive to stock-outs of required knowledge.
5. The policies of Just-In-Time (JIT) versus Just-In-Case (JIC). We will start with all generalists; then, as knowledge increases above a certain level, we will allow for mentoring beginning at ever increasing frequencies, and evaluate overall project performance.
6. The effects of employee turnover up to the loss of all employees during a project, and the best intervention mix to remedy the loss.

Future Steps: Phase III and Beyond

Knowing in advance the skills required is of critical importance to any project. However; determining a project's success solely on the basis of the levels of knowledge of its participants has not yet been accomplished and needs to be supported by research [42, 43]. Our future research phases plan to build upon integrated Phase I (inventory methodology) and Phase II (individual cognitive skill acquisition and decay) findings to improve our understanding of organizational knowledge flows. We seek to “engineer” knowledge management solutions in organizations via a *Knowledge Chain Management* approach. Our goal is to provide new theory and tools to support a contingent approaches for designing organizations to determine optimal knowledge flow interventions for a variety of task and organizational contexts.

To enable Phase III of this research effort, we build upon Nissen’s knowledge flow model below [41]. It takes as its premise that science and engineering each consistently and successfully contribute to informing practice. Precise, explanatory mathematical flow models exist in the physical sciences such as fluid mechanics, electromagnetic wave propagation and light emissions. However, in stark contrast, we are currently hindered by the imprecise and ambiguous, natural language and textual descriptions of knowledge flows [36].

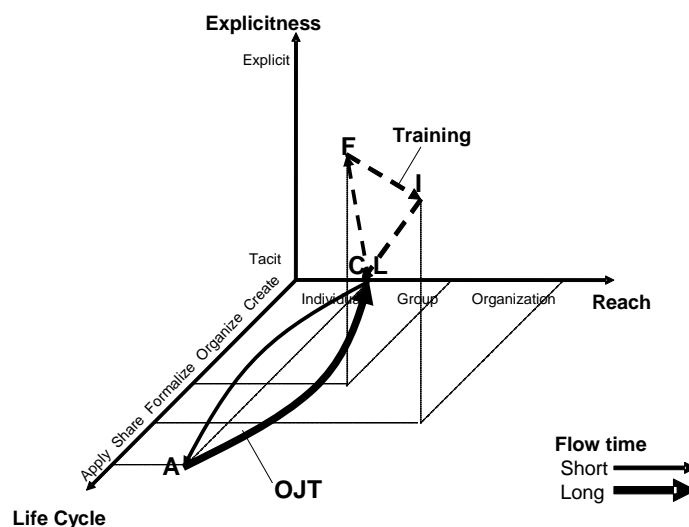


Figure 8: Nissen’s Notional Knowledge–Flow Trajectories (2006). This 4-D graph provides decision makers a means to understand and manage organizational knowledge via Knowledge Chain Management (KCM) using trajectories within the axes of *explicitness*, *reach*, and *lifecyle*.

As we consider Nissen's knowledge flow model in Figure 8, we are able to conceptualize and measure knowledge flows from given knowledge interventions (OJT, formal training, mentoring, etc.) and environmental effects (decay, interference, obsolescence, etc.). For instance, two, contrasting inflow *trajectories* are delineated in the figure: OJT and Classroom Training. The OJT trajectory is modeled as a recurring sequence of tacit knowledge application (i.e., work performance) at Point A and subsequent tacit knowledge creation (i.e., learning from work performance) at Point C. Notice this trajectory lies within the tacit plane. Alternatively, the Training trajectory rises up from the tacit plane, as knowledge is formalized (e.g., through books, course materials, computer programs), and attains broad reach, as explicit knowledge is disseminated widely through the organization. Notice also the OJT knowledge flow (esp. the learning part from Points A to C) is relatively slow (i.e., thick line in the figure) and narrow in reach (e.g., limited to individuals and small groups), whereas the Training flow (esp. after tacit knowledge has completed formalization at Point F) is relatively fast (i.e., thin line in the figure) and broad in reach (e.g., spreading organization-wide). The trajectory for mentoring (not shown) would reflect something of a combination between these two, and would have its own set of properties of interest to the manager (esp. *flow time, reach*).

We strive to provide knowledge managers with a useful methodology to perform Knowledge Chain Management (KCM). This effort begins by considering the properties of each knowledge intervention and environmental effect using Phases I and II and potentially allow optimal knowledge flows to be selected by the manager. Leveraged in a C2 environment, this methodology also has directly beneficial effects in uncoupled command and control within Edge organizations [1] by providing a method for *shared awareness*. We expect to contribute toward a more effective practice of knowledge management, and to enhance understanding of knowledge flow phenomena, by extending the capability of computational modeling to reflect knowledge flow in Edge organizations.

Conceptualization using inventory control and modeling of skill as dynamic over time has already given us new theoretical insights. It also offers potential for immediate practical application toward the management of individual and organizational knowledge [31]. We will continue our exploration of how near-optimization of knowledge and power flows can be enabled and enhanced in both military and business Edge organizations.

Conclusions

This paper describes our initial steps in specifying the key variables and variable relations necessary to apply extant skill acquisition and decay models toward understanding knowledge management. Through an extension to the POW-ER model framework we capture the dynamics of individual knowledge gained and lost in Edge organizations. The micro-behaviors found in the literature, refined by empirical behaviors observed in a set of shipboard experiments, are being embedded in the POW-ER computational model. This unique approach employs organizational simulation to validate, calibrate and refine the POW-ER parameters. We envision a line of inquiry that informs organizational learning, based on aggregated individual learning.

Phase II of this inquiry extends organization simulation research conducted by the Virtual Design Team (VDT) research group via a new simulation framework, POW-ER (Project Organization Workflow model for Edge Research). VDT agents have a static knowledge levels for each skill type modeled as an ordinal variable (None, Low, Medium, or High) [33]. The improved POW-ER framework provides development of the finer-grained, numerical skill metric, and simulates additions and deletions to agents' knowledge as knowledge inflow and outflow events and managerial interventions take place.

Integrating our findings from Phase I (micro-inventory methodologies) with Phase II (micro-dynamic, cognitive skill acquisition and decay theories) into an organizational simulation model affords a promising scientific approach to begin to "engineer" knowledge management solutions in organizations – the goal of Phase III. Once validated and, calibrated, through a set of synthetic intellectual and emulation experiments, such an extension of theory can provide researchers and practitioners a solid framework to further analyze and develop near-optimal knowledge management strategies in a variety of organizational contexts and designs.

Our over-arching goal is to identify for managers and researchers where deficiencies in knowledge flows exist prior to project commencement and help them plan in advance for project success by applying principles of Knowledge Management developed into a supply chain framework which we refer to as *Knowledge Chain Management*. Progress toward this goal will enable managers to design progressively more optimal knowledge management strategies for a variety of organizational designs in different environmental contexts.

References:

- [1] Alberts, D.S. and Hayes, R.E., *Power to the Edge*, CCPR (2003).
- [2] Anderson, J. R., *Cognitive Psychology and its Implications*, (Sixth Edition), New York, NY: Worth Publisher (2005).
- [3] Anderson, M. C., "Rethinking interference theory: Executive control and the mechanisms of forgetting," *Journal of Memory and Language*, 49 (2003), pp. 415-445.
- [4] Argote, L. "Organizational Learning: Creating, Retaining & Transferring Knowledge", Springer, 1999.
- [5] Argote, L., Beckman, S.L., and Epple, D., "The persistence and transfer of learning in industrial settings," *Management Science*, 36(2), (1990), pp. 140-154.
- [6] Barley, S. R., "Technology as an Occasion for Structuring: evidence from Observations of CT Scanners and the Social Order of Radiological Departments," *Administrative Science Quarterly*, 31(1) (1986), pp. 78-108.
- [7] Bjork, R., "Retrieval Practice and the Maintenance of Knowledge," in M.M. Grunenbug, P.E. Morris, & R. Sykes, eds., *Practical Aspects of Memory II*, London: Wiley (1988).
- [8] Bjork, R., *Retrieval as a Memory Modifier: An interpretation of negative recency & related phenomena*. In R. Solso, ed., *Info. Processing and Cognition*, New York: Wiley (1975).
- [9] Bransford, J. D., Brown, A. L., and Cocking, R. R. (editors), *How People Learn: Brain, Mind, Experience, and School*, Washington, D. C.: National Academy Press (2000).
- [10] Brill, P.H. and Chaouch, B.A., "An EOQ model with random variations in demand," *Management Science*, 41(5) (1995), pp. 927-936.
- [11] Burton, R.M. and Obel B., *Strategic Organizational Diagnosis and Design: Developing Theory for Application*, (Third Edition), Norwell, MA: Kluwer Academic (1995).
- [12] Carrillo, J. E. and Gaimon, C., "Managing knowledge-based resource capabilities under uncertainty," *Management Science*, 50(11) (2004), pp.1504-1518.
- [13] Chiesi, H., Spilich, G., and Voss, J., "Acquisition of Domain-related Info. in Relation to High & Low Domain Knowledge," *Journal of Verbal Learning & Behavior*, 18 (1979), 257-273.
- [14] Cohen, W. M. and Levinthal, D. A., "Absorptive capacity: A new perspective on learning and innovation," *Administrative Science Quarterly*, 35 (1990), pp. 128-152.
- [15] Cole, R.E., "Introduction," *California Management Review* 45(3) (1998), pp. 15-21.
- [16] Cook, K.S., Emerson, R.M., and Gillmore, M.R., "The Distribution of Power in Exchange Networks: Theory and Experimental Results," *The American Journal of Sociology*, 89(2) (1983), pp. 275-305.
- [17] Cook, S.D.N. and Brown, J.S., "Bridging Epistemologies: The Generative Dance between Organizational Knowledge and Organizational Knowing," *Organizational Science*, 10(4) (1999), pp. 381-400.
- [18] Dar-EI, E. M., Ayas, K., and Gilad, I., "Predicting performance times for long cycle time tasks," *IIE Transactions*, 27(3) (1995), pp. 272-281.
- [19] DeKeyser, R.M., "Beyond explicit rule learning: Automatizing second language morphosyntax," *SSLA*, 19, pp. 195-221.
- [20] Dierickx, I. and Cool, K. "Asset Stock Accumulation and Sustainability of Competitive Advantage," *Management Science*, 35(12) (1989), pp.1504-1511.
- [21] Ebbinghaus, H., *Memory: A contribution to Experimental Psychology*, New York: Teachers College, Columbia University (1913).
- [22] Emerson, R.M., "Power-Dependence Relations," *American Sociological Review*, 27(1) (1962), pp. 31-41.
- [23] Ericsson, K. A. and Charness, N., "Expert performance: Its structure and acquisition," *American Psychologist*, 49(8) (1994), pp. 725-747.

- [24] Grant, R.M., "Toward a Knowledge-Based Theory of the Firm," *Strategic Management Journal* 17 (1996), pp. 109-122.
- [25] Hargadon, A. and Fanelli, A., "Action and Possibility: Reconciling Dual Perspectives of Knowledge in Organizations," *Organization Science*, 13(3) (2002), pp. 290-302.
- [26] Harms, A., "Investing in People" Chief of Naval Education and Training presentation (2004), slide 5.
- [27] Hussain, F., Lucas, C., Ali, M., "Managing Knowledge Effectively", *Journal of Knowledge Management Practice*, (2004), pp. 1-12.
- [28] Jaber, M.Y. and Sikstrom, S., "A numerical comparison of three potential learning and forgetting models," *Journal of Production Economics*, 92 (2004), pp. 281-294.
- [29] Jaber, M.Y., Kher, H. V., and Davis, D. J., "Countering forgetting through training and deployment," *International Journal of Production Economics*, 85 (2003), pp. 33-46.
- [30] Jin, Y. and Levitt, R.E., "The Virtual Design Team: A Computational Model of Project Organizations," *Computational and Mathematical Organization Theory* 2(3) (1996), pp. 171-195.
- [31] Levitt, B. and March, J. G., "Organizational learning," *Annual Review of Sociology*, 14 (1988), pp. 319-340.
- [32] Levitt, R.E., "Computational Modeling of Organizations Comes of Age," *Journal of Computational and Mathematical Organizational Theory*, 10(2) (2004), pp.127-145.
- [33] Levitt, R.E., Thomsen, J., Christiansen, T.R., Kunz, J.C., Jin, Y. and Nass, C., "Simulating Project Work Processes and Organizations: Toward a Micro-Contingency Theory of Organizational Design," *Management Science* 45(11) (1999), pp. 1479-1495.
- [34] MacKinnon, D.J., Levitt, R.E., and Nissen, M.E., "Knowledge as inventory: Near-optimizing knowledge and power flows in Edge organizations (phase one)," *Proceedings International Command and Control Research and Technology Symposium*, McLean, VA, (June 2005)
- [35] McKenna, S. P. and Glendon, A. I., "Occupational first aid training: Decay in cardiopulmonary resuscitation (CPR) skills," *Journal of Occupational Psychology*, 58 (1985), pp. 109-117.
- [36] McKinlay, S., "Natural Language and the Problem of Modeling Knowledge," *Journal of Knowledge Management Practice* (2003) pp. 1-6.
- [37] Miller, G.A., "The magical number seven, plus or minus two: Some limits on our capacity for processing information," *Psychological Review*, 63, (1956), pp. 81-97.
- [38] Monge, P.R, Fulk, J., Kalaman, M.E., Flanigin, A.J., Parnassa, C., and Rumsey, S., "Production of Collective Action in Alliance-based Interorganizational Communication and Information Systems," *Organization Science*, 9(3) (1998), pp.411-433.
- [39] Nahmias, S., *Production and Operations Analysis*, (Fifth Edition), New York, NY: McGraw-Hill (2005).
- [40] Nelson, R.R. and Winter, S., *An Evolutionary Theory Economic Change* Cambridge, MA: Harvard University Press (1982).
- [41] Nissen, M. E., *Harnessing Knowledge Dynamics: Principled Organizational Knowing and Learning*, Hershey, PA: IRM Press (2006).
- [42] Nissen, M. E., "Hypothesis Testing of Edge Organizations: Specifying Computational C2 Models for Experimentation," 10th ICCRTS conference proceedings (2005).
- [43] Nissen, M., "Facilitating Naval Knowledge Flow," (2001), pp. 1-2.
- [44] Nonaka, I., "A Dynamic Theory of Organizational Knowledge Creation," *Organizational Science*, 5(1) (1994), pp. 14-37.
- [45] Pirolli, P.L. and Anderson, J.R. "The role of practice in fact retrieval," *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 11 (1985), pp. 136-153.
- [46] Polanyi, M., *The Tacit Dimension*, Garden City, NY: Doubleday (1966).
- [47] Postrel, S., "Islands of Shared Knowledge: Specialization and Mutual Understanding in Problem-Solving Teams," *Organization Science* 13(3) (2002), pp. 303-320.
- [48] Rickard, T. C., "Bending the power law: A CMPL theory of strategy shifts and the automatization of cognitive skills," *Journal of Experimental Psychology: General*, 126(3) (1997), pp. 288-311.

- [49] Rickard, T. C., "Strategy execution in cognitive skill learning: An item-level test of candidate models," *Journal of Experimental Psychology: Learning, Memory, and Cognition* 30(1) (2004), pp. 65-82.
- [50] Sackman, S. A., "Culture and Subcultures: An Analysis of Organizational Knowledge," *Administrative Science Quarterly*, 37(1) (1992), pp. 140-161.
- [51] Schott, K., "The rate of obsolescence of technical knowledge – a comment," *Journal of Industrial Economics*, 26(3) (1978), pp. 281-283.
- [52] Sikstrom, S. and Jaber, M.Y., "The power integration diffusion model for production breaks," *Journal of Experimental Psychology: Applied*, 8(2) (2002), pp.118-126.
- [53] Simon, H. A. and March, J. G., *Organizations*, New York, NY: Wiley (1958).
- [54] Smith, P. E., "Measuring Professional Obsolescence: A half-life model for the physician," *The Academy of Management Review*, 3(4) (1978), pp. 914-917.
- [55] Spender, J.C., "Making Knowledge the Basis of a Dynamic Theory of the Organization," *Strategic Management Journal* 17 (1996), pp. 45-62.
- [56] Sternberg, R. J., "Testing common sense," *American Psychologist*, 50(11) (1995), pp. 912-927.
- [57] Thomsen, J., Levitt, R.E., Kunz, J. C., Nass, C. I., Fridsma, D. B., "A Trajectory for Validating Computational Emulation Models of Organizations," *Computational & Mathematical Organization Theory*, 5 (4), 1999, pp. 385 - 401
- [58] Wagner, A. D. et al., "Building Memories: Remembering and Forgetting of Verbal Experiences as Predicted by Brain Activity," *Science*, 281, (1998), pp.1188-1191.
- [59] Walsh, J.P. and Ungson, G.R., "Organizational Memory," *The Academy of Management Review*, 16(1) (1991), pp. 57-91.
- [60] Wickelgren, W.A., "Single-trace fragility theory of memory dynamics," *Memory Cognition*, 2 (1974), pp. 775-780.
- [61] Wixted, J. T., "The psychology and neuroscience of forgetting," *Annual Review of Psychology*, 55, (2004), pp. 235-269.
- [62] Wright, T., "Factors affecting the costs of airplanes," *Journal of Aeronautical Science*, 4(4), (1936), pp. 122-128.
- [63] Zangwill, W. I. and Kantor, P. B., "Toward a theory of continuous improvement and the learning curve," *Management Science*, 44 (7), (1998), pp. 910-920.