A quantum model of dynamic interdependent uncertainties [1] for industrial organizations

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Abstract

A major failure of rational models (cognitive science, game theory) of organizations is the use of static concepts of interdependence to predict dynamic behavior. A quantum model of organizations transforms the traditional model with its dynamic interdependence of uncertainty. We consider field and laboratory data and models.

1.0. Overview:

Global economic shocks such as the rapid introduction of new technology into a mix of interdependent societies competing under various degrees of stability can produce uncertainties and risks that affect the ability of organizations to respond and adapt. In our interpretation of May (2001), as environmental volatility increases (e.g., the average volatility or VIX index on stock markets was over 30 during the recession of 2002; see www.cboe.com/micro/vix), competition and social evolution decrease in a tradeoff as dynamic stability between organizations increases; e.g., the instability among weaker U.S. commercial airlines immediately after 9/11. However, as environmental volatility reduces (e.g., the historic lows in the VIX index in 2005 with its close near 12), social evolution driven by competition increases from dynamic instability between organizations struggling to survive; e.g., the performance in small capitalization stocks in the U.S. stock market over large caps in 2004-05.

From a traditional perspective, change creates disruptive uncertainties; however, from our perspective, mergers in a market under threat attempt to increase efficiency (Andrade et al., 2001); e.g., the increased telephone market share by wireless communications led to a decrease in telephone lines in the U.S., causing mergers among telecommunication firms like that between SBC and AT&T in 2005.

Alternatively, there may be limits to static knowledge as Campbell (1996) warned for analyses based on convergence processes in the study of humans, or as Macy (2004) warned for analyses derived from invalid MAS models. But if these limitations can be controlled, the ability to anticipate the complex consequences of change may lead to a better understanding of organizational dynamics. We know that some organizations are better at managing change—e.g., Southwest versus Delta Airlines in 2005—but we do not know why. We first suspected from Luce & Raiffa (1967) that game theory is unable to distinguish between an organization's members and an aggregate of individuals. Now we know that simply summing the contributions of the agents in an organization does not tell us what an organization will do (Levine & Moreland, 1998).

Our past studies indicate that democracies and autocracies handle large-scale transformations differently. Democracies are more likely to use majority rules (MR) in their responses (Flaig, 2004), a more competitive process that generates and processes information. In contrast, organizations, coalition governments, and command economies tend to use consensus rules (CR), a more cooperative process better aimed at interpreting events to fit a single worldview such as that used by authoritarian regimes to marginalize critics; e.g., Krushchev's marginalization after criticizing Stalin (Taubman, 2004). Earlier we found that the more politically competitive was a society, the more quickly it applied its knowledge in responding to natural disasters (Lawless et al., 2006a); e.g., according to the World Bank (www.worldbank.org), China has become a financial superpower, but its autocratic government is responsible for 16 of the 20 most dirty cities around the globe, over 5,000 deaths annually in coal mining accidents, and a rural health care in collapse.

The central problem remains the lack of a mathematical theory of dynamic interdependence for social situations as when forming a dyad between two agents alters the cognitions of both. This problem was recognized early on when Von Neumann and Morgenstern (1953) acknowledged that game theory was static; while they believed that their mathematics of interdependence was a step forward, Bohr's (1955) criticism of the lack of dynamic interdependence in game theory led them to conclude that if Bohr was correct, a rational theory of behavior was "inconceivable" (p. 148).

If the factors of action and observation are interdependent and complementary, information can be collected from one factor but not both simultaneously, the flaw in presenting static game theory matrices to subjects that bedeviled Kelley (1992) and in social convergence methods that caused the great Campbell (1996) to reject his methodology which remains the mainstay of modern social science.

Shafir and LeBoeuf (2002) provide a devastating critique of the rational model's assumptions underlying traditional individual and organizational preferences, utility, choice, judgment, and decision-making. The long-held assumption in traditional cognitive science that manipulating an equivalent rational statement into one with conjunctives or disjunctives, construed with differently valenced emotions, reframed equivalently as a loss or gain, and other manipulations of the context are supposedly irrelevant to rationality have instead disabled it. In response, rationalists devised a dual cognitive systems model with intuition for everyday decisions and formal analyses for expert decisions. But Shafir & LeBoeuf found no evidence that experts are immune to violations of rationality; e.g., we criticized agent-based models of electricity markets (Conzelmann et al., 2004) based on the advice of subject matter experts as insufficient to establish validity (Lawless et al., 2006a).

Dynamic interdependence means that an agent's strategy in an interaction event shifts over the available choices over time, changing its perceptions of the risks and uncertainties. Game theory attempts to bracket expected outcomes, but it often overlooks the reactions of society and the costs of a strategy. To ask agents to justify their decisions causes them to construct answers on the fly that are independent of their decisions (Shafir & LeBoeuf, 2002). Dynamic interdependence relies on a random exploration of possible histories until the "right" one is found (stochastic resonance; Nicolis & Prigogine, 1989). To an organization provided with a dynamic interdependent metric (real-time profit and losses), such a solution often is characterized by an unexpected increase in sales (an increasing number of fourier elements to imply resolution; May, 2001). In recounting an interaction, we are left with language to provide a static description of it, or "story". But conjugate interdependence means that a "story" is unable to reconstitute the interaction.

Although complex in its ramification for mathematical or ABM models or to control, the central idea is easy to grasp with common examples: when you listen to someone else, or when you are angry and another person is not, both of you lose information about each other's states. Moreover, for our purposes, when you and another person are expressing incommensurable views to which both of you are committed for whatever reason, then the two of you become drivers on that topic in any discussion for the purpose of reaching a decision (e.g., an avowed Christian and a Muslim; a GM and a Toyota worker; and an oil executive and an environmental activist). Should other participants in this discussion and decision process be less knowledgeable than the two drivers of the discussion, they become more neutral to the discussion on technical issues.

1.1. From field research a hypotheses.

The mathematical physics of uncertainty is based on the assumption from Bohr that social reality is bistable, with multiple sources of information mostly inaccessible due to interdependent uncertainties, making social categories arbitrary. To uncover interdependent uncertain information about an organization requires that it be disturbed to generate feedback, a notion alien to rational models. A common perturbation is a hostile merger offer between competing organizations, e.g., Oracle and PeopleSoft. A common perturbation from our research of Citizen Advisory Boards (CABs) advising the Department of Energy (DOE) on environmental cleanup is the conflict caused by incommensurable beliefs, a necessary condition to attract neutrals to observe a process and determine its outcome.

One such perturbation began when Assistant DOE Secretary Roberson called for an acceleration of the cleanup in 2002, including transuranic (tru) wastes destined for WIPP (Fig. 1). In response, DOE scientists and engineers developed 13 recommendations to accelerate the disposal of Tru wastes submitted to Boards for approval; e.g., one of these recommendations was: "DOE, in consultation with stakeholders and regulators, reexamine the categorization of TRU waste using a risk-based approach" (for the list, see Lawless et al., 2005). This meant a tradeoff between leaving more dangerous tru wastes at a site, increasing risks to future stakeholders, and shipping more of it to WIPP, increasing health risk to workers and financial risks to institutions (see Fig. 1).

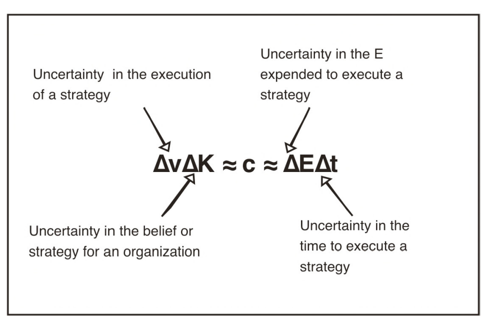


Fig. 1: The measurement problem for DOE's waste and environmental cleanup (here "c" is a constant) (Lawless et al., 2005). In response to DOE Assistant Secretary Roberson call in 2002 to accelerate DOE's cleanup, **Strategy**: Would DOE's Citizen Advisory Boards understand DOE's plan? **Execution**: Would the CAB's push DOE to execute its plan to accelerate cleanup? **Energy**: Would the CAB's support be sufficient to make DOE effective? **Time**: Would the support by the CAB's be timely or opportunistic?

From the perspective of DOE scientists and engineers, Figure 1 illustrates mathematically the effects of interdependence on uncertainty. In Figure 1, we formalized Bohr's ideas about the measurement problem as a series of interrelated tradeoffs between two sets of interdependent factors. The central idea is that as convergence is constructed in order to reduce uncertainty in one factor, say planning, the nonlinear uncertainty in the other factor is tracked mathematically. The uncertainty relations for social interaction are represented by complementarity between strategy, plans, or knowledge uncertainty, ΔK (where K = function of social and geographical location, x) and uncertainty in the rate of change in knowledge, or its execution, as $\Delta v = \Delta\ (\Delta K/\Delta t)$. Similarly, complementarity also exists in uncertainty in the energy expenditure committed to enact knowledge, ΔE, and by uncertainty in the time to enact knowledge, Δt. Bi-sided conjugate factors preclude a simultaneous knowledge of either set.

The model in Fig. 1 remained untested until the post hoc discovery that all of the Citizen Boards focused on a single problem in early 2003--accelerating tru wastes to the WIPP repository (www.wipp.carlsbad.nm.us). DOE allows its Boards to determine their own decision-making process, with five choosing majority rule (MR) and four consensus rule (CR), producing a retrospective field experiment. The result is that four of five MR and one of four CR Boards adopted the recommendations of DOE scientists, the MR boards taking about 30 minutes to decide versus 2 hours for CR boards. We have since replicated these findings in the laboratory and begun a full experiment (Lawless et al., 2006b).

1.2. Conflict and Galois lattices.

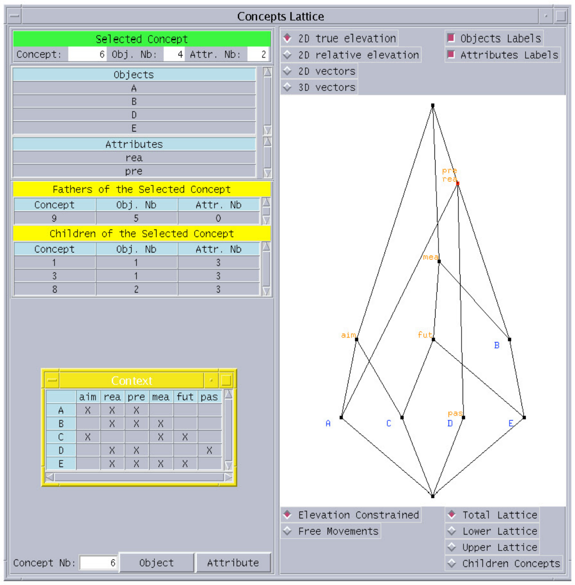
We have been building agent-based, systems and Galois lattice (GL) models of organizations of our field and laboratory findings. In this paper, we review GL models. A GL model may provide a logic structure to capture uncertainty. With humans, conflict and competition generate information and uncertainty and hold the attention of neutral observers who serve as judges. But with logic, building differential operators in symbolic models requires negation or ortho-complements that are difficult to locate in non-modular lattices (Chaudron et al., 2003). Indeed, we proved that conjunctions of first order logic literals define a non-modular lattice (the cube model). Thus, the idea is to go back to elementary properties provided by negations, considered as a GL. We intend to upgrade such structures to enrich their capabilities to capture predicate logic properties including a conflict-adapted negation operator. If problem solving is cooperative, negation locates uncertainty at the point of least cooperation between opposing agents.

As a simple first step, let us consider a GL that represents two strong participants (A,B) in an argument along the horizontal axis at two of its vertices (forming a horizontal couple). Between these two horizontal vertices, locate the infimum and supremum along the vertical axis, with the infimum at the lowest vertex and supremum at the highest, the infimum being the greatest area of agreement and lowest level of energy between participants, and the supremum the least totality of the arguments in play and highest level of energy. In this model, conflict is proportional to the energy necessary to achieve agreement on the information in play, the information missing and the size of the space containing all of the arguments; convergence occurs as the argument moves closer to one side at the expense of the other; but as convergence in the argument to one side occurs, uncertainty increases correspondingly in the other side of the argument. A solution is located in the space created by arguments between the two participants. However, the solution becomes unstable unless accepted by both participants.

As an example of a static GL, given two agents A and B strongly opposed to the following: A is opposed to the "aim" and "reasons" for a topic; B is opposed to its "reason" and "means". A context can be defined as a GL of the conflict: A verifies: "aim" and "reas"; and B verifies "reas" and "means". At the top of the lattice, the two agents both disagree on "reas", but at the bottom, it is proved that neither A nor B conflict about "aim", "reas" and "means" simultaneously, permitting conflict to be explored.

Now suppose there are three other agents C, D, and E and that if any of the agents in this society state a rejection set about a given project, it is characterized by this revised set of properties: aims, reasons, means, past, present, and future (the usual cues in a series of possible arguments related to a given project, such as: "I protest about the way this project has been conducted in the past"). Given: A aim rea pre; B rea pre mea; C aim mea fut; D rea pre pas; and E rea pre mea fut (see the picture below).

The higher we rise in the lattice, the more properties are collected (but the fewer the number of agents). In the picture, the selected red node is constituted (see upper right hand side) of agents A B D E (all but C) who all disagree on two properties of the project: "rea" and "pre" (thus, C is “neutral” to any arguments on “rea” and “pre”, making C a judge in any decision on “rea” and “pre”, a crucial link to our field research).



To extend this work and make GL’s dynamic, we will investigate Heisenberg inequalities in GL’s. Lattice logic requires that relations are logically commutative but uncertainty relations are not. However, if the GL node for an individual agent of possible conflict properties is its vector of negative preferences, and if the lattice of the social group is a conflict matrix, then one lattice matrix times another—say planning and execution—will not be commutative.

1.3. Computational coupled agent models.

For the GLA model and systems models, we believe that feedback converts a conjugate model into a limit cycle like the interdependent model of predator-prey. For a coupled model of an industrial organization, we see a 3D model with two drivers of polar opposite views fighting to persuade neutrals to adopt their interpretation of events. We follow May’s (2001) suggestion that as a landscape of potential solution space is randomly explored, increasing Fourier elements represent an increasing N (number) of supporters as the solution is discovered by stochastic resonance (e.g., Nicolis & Prigogine, 1989); e.g., Yahoo’s market success since restructuring in 2001 from 44 to 4 business units (reducing ΔK) has centered around executing search and web technology (increasing Δv), advertisement to free users, and communities of information exchange, recapturing its market leadership with about 40% of registered global web users.

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