	Supporting Material is available for this work. For more information,	follow t	he li:	nk from
2	the Table of Contents to "Accessing Supporting Material".			

# Collaborative law dynamics: *collegiality* in civil litigation?

Nicholas C Georgantzas *Fordham University Business Schools* 113 West 60th Street, Suite 617-D New York, NY 10023-7484, USA Tel: (+917) 667-4022 E-mail: georgantzas@fordham.edu Andry Karpasiti Argyrides *Strategic Scenarios, Inc.* Sandcastle Key, Suite 210 Secaucus, NJ 07094-2207, USA Tel: (+201) 456-2536 E-mail: ssi@StrategicScenarios.com

*Abstract*—In the Markovian paradoxical games that unfold in business and civil litigation, participants choose between collegiality and discord tactics. In business, for example, managers accomplish tasks either by working collaboratively or by working alone. Similarly, in civil litigation, lawyers can choose collegiality to resolve conflict amicably or, alternatively, use discord to producer even more conflict. Four system dynamics game models help explore the dynamic repercussions of these two means of conflict resolution in business and civil litigation. The models portray two-contestant, paradoxical self-referential games of non-constant sum (one's loss is not automatically the other's payoff) conflicts. Two players or groups compete with dynamic (time varying) probabilities of collaboration. Their game is paradoxical because both parties can either win or lose simultaneously. It is selfreferential when the payoff, prior discord and loss parameters depend on the players' collaboration probabilities. Past research has found similar game models with exogenous parameters to be conservative, possessing two centers around which games can oscillate forever. But with endogenous parameters the dynamics becomes dissipative, possessing a single fixed-point attractor of moderate equal gains. Large subsets of initial discord tactics converge on the fixed-point attractor to sustain collegiality equilibria. The game ends once the point attractor has absorbed all dynamics, leaving the system in a stable, negative feedback state. If both players collaborate without undue bias and preconceived opinions, and equally discount each other's collegiality or lack of it, then the stable attractor moves closer to maximum payoff, where both parties collaborate with probability 1 (one). In the asymmetric model, however, one of the players can take less into account the other's collegiality or discord tactics. Then, it is the most impartial player or group that profits the most!

## Keywords: civil litigation, collaborative law, collegiality, conflict, Deming, game theory, system dynamics

A lmost everyone in business can benefit from improved negotiating skills. And 'management by cooperation' might best articulate Deming's thinking in the late 1980s and early 1990s. Deming (2000) talks about 'win-win' situations in a *new climate*, diametrically opposed to the 'I win-you lose' attitudes that the competitive rivalry ethic stimulates. According to the OQPF Roundtable (2000), rivalry produces win-lose results, whereas collegiality and collaboration among individuals and organizational units can produce win-win, all-gain results for the benefit of all concerned. The tactics that produce win-win results require not only commitment to collegiality and teamwork, but also the removal of reward systems that promote local optimization and global system damage.

Yet, sustaining organizational change is tough. Organizational process improvements show a *start and fizzle* pattern so frequently that organization researchers use it as a reference mode to develop dynamic hypotheses about change (Morrison 2001). The idea appears in many guises throughout organization theory, widely recognizing the tendency for changes to run out of energy and to lose momentum almost as soon as they begin. Change efforts that foster learning among people, and build understanding of processes and skills for collaborating effectively, in turn lead to benefits in subsequent collaborative efforts (Morrison 2002).

In the more specific context of civil litigation, conflict is the heart and soul of the law. To help manage conflict, rules of law have been prescribed to govern human interaction. In essence, the function of the law is to establish:

rules and procedures that constrain the power of all parties, hold parties accountable for their actions, and prohibit the accumulation of autocratic or oligarchic power. It provides a variety of means for the non-violent resolution of disputes between private individuals, groups, or between those actors and the government (Crocker and Hampson 1996, p. 586).

If the role of law is to resolve conflict, then how is it that the system in which the law functions is itself the producer of more conflict? On a closer look, the civil judicial system is inherently adversarial. Consequently, the behavior of two adverse parties fighting for their desired outcomes pretty much defines its organizational makeup. It is somehow perceived that one's gain is another's loss and this becomes the guiding force in resolving legal disputes. Erroneously, policies that govern the judicial process are premised on constant-sum war games (Nicolis 1986, pp. 218-222), where the litigants strive to achieve desired results alone rather than through collaboration.

When the litigation parties act as opponents, their behavior dynamics differs from that of participants who choose to collaborate. When they choose to file a lawsuit, to take discovery, to file motions, to decline settlement offers and to appeal, the players engage in a duel where one's death is another's victory. Engaging in a duel, the opponents undertake a certain risk. So, understanding litigants' proclivities for risk is essential to understanding their behavior, the nature of litigation, and the likely impact of changes in the civil justice system (Rachlinski 1996).

The notable Chief Justice Warren E. Burger notes: "our litigation system is too costly, too painful, too destructive, too inefficient for a civilized people" (*c.f.* Arnold 2000). Collegiality, a value bestowed upon the civilized world, is not exactly what characterizes litigation. Instead, litigation, particularly the pre-trial phase of the process (Table 1), provides the battlefield for a combat to be won, not a dispute to be resolved. To collaborate for a mutually desirable outcome is an anathema for those proponents of litigation who consider collaboration a concession of weakness.

This paper combines game theory with system dynamics to answer client concerns about these issues. The client is the in-house counsel of a large insurance firm, which finds that its lawyers spend too much time in disputes during the pre-trial phase of the civil litigation process (Table 1). Four system dynamics game models help explore the dynamic consequences of choosing between collegiality and discord tactics as the means of conflict resolution in business and civil litigation. The models depict Markovian paradoxical games with two players or groups. Paradoxical self-referential games are non-constant sum (one player's loss is not automatically the other's payoff) conflicts, where the two players or groups compete with dynamic (i.e., time varying) probabilities of collaboration. Their game is paradoxical because both parties can either win or lose simultaneously.

It becomes self-referential when the payoff or 'tempting' parameters, and the prior discord and loss coefficients depend explicitly on the participants' collaboration probabilities.

	Phase		Action Content		Specific Task
1	Pleadings	1	Cause of Action	1	Breach of promise
	-		·	2	Breach of duty
		2	Complaint	1	Jurisdiction stated
			•	2	Basis in fact and law
				3	Relief requested
				•	SERVICE OF PROCESS
		3	Answer	1	Admit or deny
				2	Affirmative defense
				3	Counterclaims
				4	Other
2	Pre-Trial	1	Discovery	1	Interrogatories
				2	Request for admissions
				3	Depositions
				4	Other
	Ö	2	Motions	1	No cause of action
				2	Compel discovery
				3	Summary judgment
				4	Other
		3	Pre-Trial Conference	1	Focus issues
				2	Settlement
				3	Schedule
3	Trial	1	Jury Selection	1	Challenge for cause
				2	Peremptory challenges
		2	Trial	1	No cause of action
				2	Compel discovery
				3	Summary judgment
				4	Other
		3	Verdict	1	Jury instructions
				2	Preponderance of evidence
				•	JUDGMENT
				1	Award
				2	Judgment with standing verdict (JNOV)
4	Post-Trial	1	Motion for New Trial	1	Error of law
				2	Error of conduct of trial
		2	Appeal	1	Record of trial
				2	Briefs
				3	Oral arguments
				4	Decision
		3	Enforcement	1	Order to pay writ of execution
				2	Take property writ of execution

Table 1 The civil litigation process

Past research (Nicolis 1986, Nicolis, Bountis and Togias 2001, Rapoport 1966, Swingle 1970) has found two-contestant paradoxical self-referential game models with exogenous parameters to be conservative, possessing two centers around which games oscillate forever. When the payoff, prior

discord and loss parameters vary endogenously, however, then the dynamics becomes dissipative, possessing a single fixed-point attractor of moderate equal gains. Large subsets of initial discord tactics converge on this attractor to attain constant probabilities of collaboration (Nicolis et al. 2001).

Conventional wisdom suggests that payoff, prior discord and losses are causally prior to collaboration probabilities. But our results suggest that causality might indeed run in both directions. Its causal loop worldview makes system dynamics uniquely suited to the task of computing win-win scenarios in business and civil litigation, tying their pieces together into an account of the social world that is far more generative and empowering than alternatives based on conventional economic logic. Perhaps the "somewhat critical manner" (Forrester 2003, p. 331) in which system dynamicists approach economics and operations research keeps them isolated from economics and operational research (OR). But Sterman's principle #4 for the successful use of system dynamics states:

**System dynamics does not stand alone. Use other tools and methods as appropriate**. Most modeling projects are part of a larger effort involving traditional strategic and operational analysis, including benchmarking, statistical work, market research, etc. Effective modeling rests on a strong base of data and understanding of the issues. Modeling works best as a complement to other tools, not as a substitute (Sterman 2000, p. 80).

Moreover, according to Repenning:

Other communities in the social sciences maintain different worldviews, ... but our [system dynamics community] worldview is more consistent with those in psychology, sociology and anthropology. We should not abandon our efforts to become better connected with our colleagues in economics and operations research (Repenning 2003, pp. 319-320).

Following the background section below, the paper shows a system dynamics interpretation of four paradoxical self-referential game models by Nicolis et al. (2001). Causal tracing and partial loop analyses embellish model description as it moves from exogenous payoff, prior discord and loss parameters to endogenous, time-varying coefficients to symmetric and *asymmetric impartiality* with respect to each player's attention to the other's collegiality (or lack of it). The simulation results section follows the same progression as the model description does, but also looks at the four model variants in terms of their shifting loop polarity and prominence (Richardson 1995).

The paper goes beyond merely translating the work of Nicolis (1986) and Nicolis et al. (2001) into system dynamics models and replicating their results. The results section dares to ask how and why the models produce the result they do. Mojtahedzadeh's (2001) *Digest* ® software allows going beyond *dynamic* and *operational thinking*, to seek insight from system structure and, thereby, to accelerate *circular causality thinking* (Richmond 1993).

The results show how shifting loop polarity and prominence determine system behavior in the exogenous, constant parameter model. But once endogenous, the parameters vary along with the players' collaboration probabilities. Then time-shifting prominent loops determine system behavior. In the latter model, the game ends once a fixed-point attractor has absorbed all dynamics, leaving the system in a stable, negative feedback state. If both players collaborate free from undue bias and preconceived opinions, equally disregarding each other's collegiality or lack of it, then the stable attractor moves closer to the state of maximum payoff and both parties collaborate with probability 1 (one). In the *asymmetric* model, however, where one of the players takes less into account the other's collegiality, is the most impartial player or group that profits the most!

#### **Background research and methods**

Fisher, Ury and Patton (1991) offer practical guidelines for business executives and lawyers dealing with each other, with superiors and staff, with customers, partners, suppliers and with government regulators. Although non-academic, their book can help negotiate with a powerful other side that refuses to play or uses dirty tricks. The authors explain the problems that arise from bargaining over positions and present an approach that revolves around four elements: (a) separate the people from the problem, (b) focus on interests, not positions, (c) invent options for mutual gain and (d) insist on using objective criteria. Behind this 'principled negotiation' approach is the belief that when each side comes to understand the interests of the other, they can jointly create options that are mutually advantageous, resulting in a wise settlement.

This same belief seems to drive the work on the economics of litigation that originated with a trio of articles published in the early 1970s (Gould 1973, Landes 1971, Posner 1973). Subsequently, Shavell (1982), and then Priest and Klein (1984) made significant contributions to the field. Namely, Priest and Klein (1984) predict, for example, that suits that fail to settle before trial will have a 50 percent chance of a plaintiff's verdict. Shavell (1982) shows the economic divergence of private and social goods in litigation. Cooter and Rubinfeld (1989) provide an excellent review of this literature.

Over the past twenty-five years, the law and economics field has produced a fairly consistent framework describing litigants' behavior, but failing to paint a complete picture of litigation dynamics. That is, the field relies on the 'rational model' of decision making, i.e., the 'expected utility' model. All of the economic models of suit and settlement depend on the assumption that the litigation process enables choices designed to give litigants the best possible outcomes.

This paper questions this assumption. Modifying the economic model by incorporating collaboration into the dynamics of dispute resolution might create a richer and more accurate sense making of a complex and changing world. In fact, our results show that regardless of the adversaries' initial positions, both of them can win in the long run in terms of both time and money.

These results support the work of lawyer Stuart G. Webb of Minneapolis, Minnesota, the founder of collaborative law (Bushfield 2002). In 1990, after 15 years of practicing 'traditional' family law, Webb decided to do something about the frustration and stress he and his clients were experiencing (McArdle 2004). He decided to 'unilaterally disarm'. He announced that he would no longer go to court on behalf of matrimonial clients. He would do his best to help them settle their problems through negotiation, but if negotiation proved unsuccessful and either spouse commenced court proceedings, he would withdraw from the case and refer his client to a lawyer with a more litigious temperament. Other lawyers in Minneapolis found the concept intriguing. A group of them decided to follow Webb's lead. They formalized the idea by preparing a contract that both lawyers and both spouses would sign, committing the four parties to negotiate diligently and in good faith, and requiring the lawyers to withdraw from the case if it went to court.

Collaborative law is becoming the practice of law by interdisciplinary problem solving that does not include adversarial techniques or tactics. Based on being proactive, seeks first to understand and then to be understood. It uses a cooperative mode of negotiation and neutral experts to resolve conflict. The field is gaining momentum and attention. Perhaps the most profound development in the legal profession, adds yet another way to alternative dispute resolution, and shares a commitment to achieving settlement without the use of any form of litigation. But exactly how does it work?

Collaborative law is a process whereby dispute parties and their attorneys agree to resolve the dispute without going to court. The attorneys assist the parties in resolving their own conflict through cooperative tactics rather than adversarial techniques and litigation. Early non-adversarial participation by the attorneys allows them to use lawyering skills ordinarily stunted by litigation, such as analysis and reasoning to solve problems, to generate options, and to create a positive context for settlement. The process is designed to empower clients to fashion agreements that address their unique concerns and to produce results more creative than and superior to what the clients experience in an adversarial process. It consists of a series of informal 'four-way' settlement meetings held among the participants to consider various options and to resolve issues collegially. Each party is represented and guided at all times by his or her own counsel, who is an experienced lawyer trained in the collaborative or cooperative approach to solving problems. The goal is to enable parties to reach a fair and reasonable settlement that addresses and meets the needs of all parties, rather than, for example, that of the squeakiest wheel or the most aggressive player.

Strong commitment to collegiality typifies collaborative law, founded on honesty, cooperation, integrity and professionalism, and geared toward the future well being of all concerned. All parties agree to provide full and honest disclosure of all information to each other. Where positions differ, all participants use their best efforts to create proposals that meet the fundamental needs of both parties and, if necessary, they compromise to settle all issues. The benefits of engaging in the process of collegial dispute resolution are: 1) it is less costly than litigation, 2) it is less time-consuming, 3) a climate of cooperation reduces the stress that accompanies litigated disputes, 4) disagreements are resolved in a climate of confidentiality, and 5) each player is a vital part of the settlement, not an adversary.

In this context, two-contestant games have long been researched since the *Trucking Game* of Deutsch and Krauss (1960). Swingle (1970) surveys many situations that create the possibilities for such conflicts to emerge. Players do not look to game-theorists for moral principles; they already have their own. But it is possible to frame the paradoxical, self-referential games that unfold in business and civil litigation using discrete-time Markov chains. Courcoubetis and Yannakakis (1988) and Hansson and Jonsson (1994), for example, investigate models for discrete-time Markov chains. Large classes of stochastic systems operate, however, in continuous time. So, continuous time Markov chains form a useful extension in a generalized framework for decision and control (Ross 1983).

Psycho-physiological research and evidence (Gershon et al. 1977, Wolf and Berle 1976) as well as trends in psychosomatic medicine (Hill 1976) encouraged Nicolis (1986) to study hierarchical systems in human communication (Watzlawick et al. 1967). Given that all human cognitive levels use the same hardware, namely groups of collaborating neurons and tissues, Nicolis focused on collaborative communication regimes that weigh homeostatic probabilities as they strive to maximize a pre-selected 'figure of merit' or payoff. To quantize the state space at each hierarchical level, Nicolis replaced the stochastic nonlinear differential equations that correspond to continuous state descriptions with discrete-time Markov chains. The transition matrices that characterize these chains fully describe the transitions among all possible system states at each hierarchical level (Nicolis 1986, pp. 184 and 377-378).

Following Rapoport (1966), and with the help of *Itô* stochastic differential equations, *Wiener-Lévy* processes and the *Fokker-Planck-Kolmogorov* equation, Nicolis (1986) and Nicolis et al. (2001) propose a logic for specifying properties of such systems and describe decision procedures. Essentially building on the work of Nicolis (1986) and Nicolis et al. (2001), this paper's system dynamics model structures show a generic logic for modeling paradoxical self-referential games as continuous time Markov chains.

Mojtahedzadeh's (2001) *Digest*® software computes a model's pathway participation metric (PPM) to help detect and display prominent causal loop structures or pathways. Mojtahedzadeh (1996) developed the PPM mathematical algorithm to discover which pathway leading into a variable of interest contributes the most to generating the dynamic behavior pattern of that variable through time. PPM computes the selected variable dynamics from its slope and curvature, i.e., its first and second time derivatives. It is not a secret that, without computer simulation, even experienced modelers find it hard to test their intuition about the connection between circular causality and system dynamics. Using the *Digest*® software is, however, a necessary but insufficient condition for creating *insightful system stories*. The canon? Insightful system stories demand integrating insight from *dynamic*, *operational* and *feedback loop thinking* (Mojtahedzadeh 2001, Richmond 1993).

#### Model description with causal tracing and partial causal loop analysis

By extending Rapoport's (1966) work on human behavior and decision making through cyberneticmathematical analysis, Nicolis (1986) deduced the dynamics of communication system hierarchies as the 'offshoot' of an underlying game between two players involved in alternating plays with set rules. Figure 1 shows the two-contestant (i = 1, 2) 2×2 payoff matrix, Markov chain diagram, conditional probabilities or 'propensities' for collegiality and discord,  $C_i$  and  $D_i$ , respectively, by players i = 1, 2, and the transitional probabilities  $P_{ji}$ , according to which the game states  $S_j$ , j = 1, 2, 3, 4, shift from state  $S_i$  to  $S_i$ .

The lower-left and upper-right triangles of the matrix squares (Fig. 1a) show the payoff (+ sign) and loss (- sign) coefficients, which determine the conditional probabilities or 'propensities' for collegiality and discord,  $C_i$  and  $D_i$ , respectively, for players i = 1, 2. The  $\beta_1$  and  $\beta_2$  parameters are the players' tempting factors. They reflect the expected payoff of the first and second player, respectively, when they employ discord tactics and thereby move into the states  $S_2$  and  $S_3$  of Fig. 1a. The same parameters correspond to losses  $-\beta_i$  when one player chooses collegiality and the other chooses discord. Both factors are unity as state  $S_1$  but become losses of magnitude  $-k_i\beta_i$  at state  $S_4$ , where both players choose discord tactics, with loss coefficients  $k_i > 1$ , i = 1, 2.

In his treatment of hierarchical systems, Nicolis (1986) derived both the conditional and the transition probabilities of Fig. 1c and 1d. Given that the two players were at state  $S_j$  (j = 1, 2, 3, 4) at a previous step, in such Markovian paradoxical games Nicolis (1986) and Nicolis et al. (2001) define the conditional probability  $X_i$  that the *i*th player (i = 1, 2) collaborates using the equations of Fig. 1c. Figure 1d shows the transition  $P_{ji}$  probability products as the game shifts from state  $S_j$  to state  $S_i$ . If both players had collaborated in a collegial fashion at the previous step, i.e., their game were at state  $S_1$ , then  $X_i$  denotes their collaboration probabilities. If the last step was, however, in any state  $S_j$  other than  $S_1$ , then the  $d_i$  parameter designates these probabilities.

Figure 1 The i = 1, 2 contestant (a)  $2 \times 2$  game matrix, (b) Markov chain, (c) conditional *propensities* for collegiality  $C_i$  and discord  $D_i$ , and (d) transition probabilities  $P_{ji}$ , as the game shifts from state  $S_i$  to  $S_i, j = 1, 2, 3, 4$  (adapted from Nicolis 1986 and Nicolis et al. 2001)



Garnished with cartoons per Sterman's (2000, 210) suggestion, Fig. 2a shows the stock and flow diagram of the collaboration probabilities  $X_i$  model sector, with *exogenous* payoff  $\beta_i$ , prior discord  $d_i$  and loss  $k_i$  parameters, i = 1, 2. Figure 2b shows the sector of the state  $S_j$  occupancy probabilities  $u_j, j = 1, 2, 3, 4$ , in the payoff functions  $G_i, i = 1, 2$ . And Table 2 shows the equations of both model sectors.

Figure 2 Stock and flow diagrams of the (a) collegiality probabilities  $X_i$  of players i = 1, 2 and (b) state  $S_i$  occupancy probabilities  $u_i$ , j = 1, 2, 3, 4, in the payoff functions  $G_i$ , i = 1, 2



Stocks or Level Variables	Equation #
$X_1(t) = X_1(t - dt) + (\Delta x_1) * dt \{unitless\}$	(1)
INIT $X_1 = 0$ {unitless}	(1.1)
$X_2(t) = X_2(t - dt) + (\Delta x_2) * dt {unitless}$	(2)
INIT $X_2 = 1 - X_1$ {unitless}	(2.1)
Flows or Rate Variables	
$\Delta x1 = (a_1 * X_2 ^2 + b_1 * X_2 + c_1) * (X_1 * X_2 - d_1 * d_2 - 1) ^(-2) / t \{unit = 1 / day\}$	(3)
$\Delta x2 = (a_2 * X_1 ^2 + b_2 * X_1 + c_2) * (X_1 * X_2 - d_1 * d_2 - 1) ^(-2) / t \{unit = 1 / day\}$	(4)
Auxiliary Parameters or Converters	
$a_1 = d_1 * d_2 * \beta_1 * (k_1 + 1) {\text{unitless}}$	(5)
$a_2 = d_1 * d_2 * \beta_2 * (k_2 + 1) {unitless}$	(6)
$b_1 = -k_1 * \beta_1 * d_1 * d_2 * (1 + d_1 + d_2) + d_1 * d_2 * \beta_1 * (d_1 - d_2) + d_1 * d_2 \{unitless\}$	(7)
$b_2 = -k_2 * \beta_2 * d_1 * d_2 * (1 + d_1 + d_2) + d_1 * d_2 * \beta_2 * (d_2 - d_1) + d_1 * d_2 \{unitless\}$	(8)
$c_1 = (d_1 \land 2) * (d_2 \land 2) * \beta_1 * (k_1 - 1) + d_1 * d_2 * \beta_1 * (k_1 - 1) {unitless}$	(9)
$c_{2} = (d_{1} \land 2) * (d_{2} \land 2) * \beta_{2} * (k2 - 1) + d_{1} * d_{2} * \beta_{2} * (k_{2} - 1) \{unitless\}$	(10)
Exogenous Auxiliary Constants	
$   \beta_1 = 4 \{ unitless \} $	(11)
$\beta_2 = 4 \{ unitless \}$	(12)
$d_1 = 0.5 {unitless}$	(13)
$d_2 = 0.5 {unitless}$	(14)
$\mathbf{k}_1 = 1.2 \{ \text{unitless} \}$	(15)
$k_2 = 1.2 {unitless}$	(16)
$t = 6 \{days\}$	(17)

Table 2 Collaboration, state occupancy probability, and payoff or loss equations for players i = 1, 2

(a) Collaborati	on probability $\lambda$	$C_i$ equations,	with exogenous	parameters $\beta_i$ ,	$d_i$ and $k_i$ , $k_i$	i = 1, 2
-----------------	--------------------------	------------------	----------------	------------------------	-------------------------	----------

(b) Payoff or loss function  $G_i$ , i = 1, 2, and state  $S_j$  occupancy probability  $u_j$ , j = 1, 2, 3, 4, equations

Auxiliary Parameters or Converters	
$G_1 = u_1 - k_1 * \beta_1 * u_4 + \beta_1 * (u_3 - u_2) $ {unitless}	(18)
$G_2 = u_1 - k_2 * \beta_2 * u_4 + \beta_2 * (u_2 - u_3) {\text{unitless}}$	(19)
$\sum = X_1 * X_2 - d_1 * d_2 - 1 \{ \text{unitless} \}$	(20)
$\mathbf{u}_1 = -\mathbf{d}_1 * \mathbf{d}_2 / \sum \{ \text{unitless} \}$	(21)
$u_{2} = (-d_{1} * d_{2} * X_{1} + d_{1} * X_{1} * X_{2} + d_{1} * d_{2} - d_{1}) / \sum \{\text{unitless}\}$	(22)
$u_{3} = \left(-d_{1} * d_{2} * X_{2} + d_{2} * X_{1} * X_{2} + d_{1} * d_{2} - d_{2}\right) / \sum \left\{\text{unitless}\right\}$	(23)
$u_4 = \left( (1 - d_1 - d_2) * X_1 * X_2 + d_1 * d_2 * (X_1 + X_2 - 2) + d_1 + d_2 - 1 \right) / \sum \left\{ \text{unitless} \right\}$	(24)

The collaboration probability  $X_i$  stocks (Eqs 1 and 2) are the deterministic, unitless outcomes of the rate equations 3 and 4 of Table 2. Nicolis (1986) and Nicolis et al. (2001) derive both the flows

(Eq. 3 and 4) and the auxiliary parameters (Eq. 5 through 10 of Table 2a and Fig. 2a) from the players' payoff functions  $G_i$ , i = 1, 2 (Fig. 2b and Eqs 18 and 19 of Table 2b). Apparently, the Markovian kinetics does not evolve under fixed propensities, such as the exogenous, constant, prior discord parameters  $d_i$ , i = 1, 2 (Eq. 13 and 14, Table 2a). Learning must take place as the system of differential equations 3 and 4 (Table 2a) governs the time evolution of the players' propensities for collegiality, as litigants and collaborative law proponents play their games in iterations.

Knowledge management in system dynamics begins by differentiating stocks from flows and how stocks and other variables and parameters determine the flows. Identifying the integration points facilitates understating one source of dynamic behavior in the system. The stock and flow diagram of Fig. 2 shows accumulations and flows essential in generating the dynamic behavior of players in the pre-trial phase of the civil litigation process (Table 1). It also tells, with the help of the Table 2 equations, what drives the flows in the system. Stock and flow diagrams like the one of Fig. 2 help accelerate what Richmond (1993) calls *operational thinking*.

But stock and flow diagrams do not automatically unearth which balancing or negative (–) causal loops and which reinforcing or positive (+) loops govern the system. Causal loop or influence diagrams (CLDs or IDs) are the tools that convey information about circular causality. With dynamic thinking *implicitly* present (Richmond 1993), the causal tracing and partial loop analysis of Fig. 3 can begin to accelerate feedback loop thinking by exploring exactly how the system's causal structure causes its behavior, as players learn by playing their game iteratively.

Figure 3 Causal tracing and partial loop analysis with exogenous parameters



#2	1	$X_2 \xrightarrow{\sim} \Delta x_2$	Balancing (-)
#3	3	$X_1 \xrightarrow{\cdot} \Delta x_2 \xrightarrow{\cdot} X_2 \xrightarrow{\cdot} \Delta x_1$	Reinforcing (+)

The causal tracing of  $X_1$  ( $X_2$  is symmetric), causal loop diagram and partial loop analysis of Fig. 3 show how situations that call for collegiality in business and civil litigation might initially look simple, as long as the payoff, prior discord and loss parameters are exogenous. Three causal loops govern the time evolution of the players' propensities for collaboration: two balancing or negative (–) loops (#1 and #2, Fig. 3), and one positive (+) or reinforcing loop (#3, Fig. 3).

## Endogenous parameter (complete self-reference) model

The more complex and realistic model of paradoxical self-referential games in business and civil litigation calls for the  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2 parameters of Fig. 2 and Table 2 to depend on the  $X_i$  stocks. Figure 4 and Table 3 show the revised collaboration probability  $X_i$  model sector and sector equations, respectively, with the now *endogenous* parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2. The *ghosted*  $X_1$  and  $X_2$  stocks (lower middle, Fig. 4) now enter Eq. 25 through Eq. 30 of Table 3, which replace the exogenous constant parameters of Fig. 2a and Table 2a (Eq. 11 through Eq. 16, Table 2a).



Figure 4 Revised  $X_i$  model sector, now with *endogenous* parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2

The  $X_i$  stocks are still the probabilities of collegiality and collaboration given that both players collaborate. And the  $d_i$ , i = 1, 2 prior discord coefficients still hold prior lack of collegiality probability values when at least one player had previously chosen discord. If the  $X_i$  stocks increased (decreased), then the  $d_i$  values would increase (decrease) too. The revised  $d_i$  equations (Eq. 27 and Eq. 28) of Table 3 assume that both players equally notice each other's collegiality or lack of it. Similarly, the equations of the now endogenous payoff  $\beta_i$  and loss  $k_i$ , i = 1, 2 parameters of Fig. 4 and Table 3 (Eqs 25, 26, 29 and 30) show that players will choose collegiality and collaboration when less payoff and more losses result from choosing discord. Self-reference favors collegiality: decreasing  $\beta_0$  (Eq. 31) decreases payoff and increasing  $k_0$  (Eq. 32) increases the losses from choosing discord tactics.

Endogenous Auxiliary Parameters or Converters	Equation #
$\mathfrak{K}_1 = \mathfrak{K}_0 / (X_1 + X_2 + 1) \{\text{unitless}\}$	(25)
$\mathfrak{K}_2 = \mathfrak{K}_0 / (X_1 + X_2 + 1) \{\text{unitless}\}$	(26)
$d_1 = (X_1 + X_2)  /  2  \{ \text{unitless};  0 \le d_1 \le 1 \}$	(27)
$d_2 = (X_1 + X_2) / 2 \{ unitless; 0 \le d_2 \le 1 \}$	(28)
$k_1 = k_0 + (X_1 + X_2) / 2 \{unitless\}$	(29)
$k_2 = k_0 + (X_1 + X_2) / 2 \{unitless\}$	(30)
Exogenous Auxiliary Constants	
$ \mathfrak{K}_0 = 4 \{ unitless \} $	(31)
$k_0 = 1.2 \ \{\text{unitless}; 1 \le k_0 \le 2\}$	(32)

Table 3 Revised  $X_i$  model sector equations, with *endogenous* parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2

Figure 5a shows the causal tracing about the  $X_1$  stock ( $X_2$  is symmetric), and Fig. 5b the causal diagram and partial loop analysis with the now endogenous parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2. Comparing Fig. 5 with Fig. 3 shows how drastically the 'reachability' of the  $X_1$  stock has increased and so has the model's dynamic complexity owed to the *endogeneity* of these six parameters.

Figure 5a Causal tracing about  $X_1$ , with *endogenous* parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2





Figure 5b Partial loop analysis, with *endogenous* parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2

Both *iThink* (Richmond et al. 2004) and *Vensim* PLE (Eberlein 2002) agree that parameter endogeneity causes the number of loops that determine the players' propensities for collegiality and collaboration to increase from three (Fig. 3) to 208 (Fig. 5b) loops per player. To illustrate the increase in system complexity through a couple of causal loop examples, Fig. 5b shows the last two loops in which the  $X_1$  stock plays a part. Both loops are of length seven, but causal loop #207 is balancing or negative and loop #208 a positive or a reinforcing one.

#### Symmetric impartiality model

The exogenous impartiality or 'indifference' parameter p ( $0 \le p \le 1$ ) of Fig. 6a and Eq. 37 (Table 4) allows assessing the situation where both players become symmetrically unbiased toward each other's collegiality or propensity to collaborate and initial discord tactics. As p decreases, each player becomes *equally*, i.e., symmetrically, more indifferent toward the other, free to collaborate collegially, without undue bias and preconceived notions.

Table 4 shows exactly how this exogenous p ( $0 \le p \le 1$ ) affects the endogenous parameters  $\beta_i$  and  $d_i$ , i = 1,2 (Eq. 33 through Eq. 36) in the model of symmetric impartiality (Fig. 6a). Naturally, when p = 1, then the model reverts to the endogenous parameters one (Fig. 4 and Table 3). But it might prove interesting to look further into this impartiality phenomenon *asymmetrically*.

Figure 6 Causal structure modifications of Fig. 4 for (a) symmetric and (b) asymmetric impartiality



Table 4 Effects of the exogenous parameter p ( $0 \le p \le 1$ ) on the endogenous  $\beta_i$  and  $d_i$ , i = 1, 2 parameters in the symmetric impartiality model (Fig. 6a)

Endogenous Auxiliary Parameters or Converters	Equation #
$\beta_1 = \beta_0 / (X_1 + p * X_2 + 1) $ {unitless}	(33)
$ \mathfrak{K}_2 = \mathfrak{K}_0  /  (p \ast X_1 + X_2 + 1)  \{ unitless \} $	(34)
$d_1 = (X_1 + p * X_2) / 2 \{unitless\}$	(35)
$d_2 = (p * X_1 + X_2) / 2 \{unitless\}$	(36)
Exogenous Auxiliary Constant	
$p = 0.9 \text{ {unitless; } 0 \le p \le 1 }$	(37)

## Asymmetric impartiality model

So far, the game model variants of Fig. 2a, Fig. 4 and Fig. 6a have shown symmetric structures, where the game dynamics would have been invariant if the two players were to swap positions. But the endogenous parameter q ( $0 \le q ) of Fig. 6b and Eq. 40 (Table 5) now takes the place of <math>p$  in Eq. 38 and Eq. 39 of Table 5, which replace Eq. 34 and Eq. 36 on Table 4, respectively.

Table 5 Effects of the *endogenous* parameter q ( $0 \le q ) on the$ *endogenous* $<math>\beta_2$  and  $d_2$  parameters in the *asymmetric* impartiality model (Fig. 6b)

Endogenous Auxiliary Parameters or Converters	Equation #
$\beta_2 = \beta_0 / (q * X_1 + X_2 + 1) $ {unitless}	(38)
$d_2 = (q * X_1 + X_2) / 2 \{unitless\}$	(39)
$q = 0.95 * p \{ unitless; (0 \le q$	(40)

This way q helps assess what would happen if one player were to account less for the other player's collegiality or propensity to collaborate. With q in place, the model permits one to treat the effects the two players might have on one another independently. In order to assess how sensitive 'where the game ends' is to such effects, for example, one might set the endogenous parameter q=0.95p as in Eq. 40 (Table 5), and then let the exogenous parameter p vary in Eq. 37 (Table 4). Making it so moves the game's single fixed-point attractor off its symmetric impartiality location, so the more impartial player or group profits the most!

## Simulation results with prominent structure and polarity analysis

Dynamic thinking is implicit in feedback loop thinking (Richmond 1993). Each circular causal loop structure has, however, its own behavioral implications, so the overall dynamics of model structure remains unclear until computer simulation comes to the rescue. In addition to helping one draw stock and flow diagrams and count multitudes of feedback loops on the glass of computer screens, iTbink (Richmond et al. 2004) and Vensim PLE (Eberlein 2002) make dynamic thinking *explicit* through repeated simulation runs.

Figures 7 and 8 show the comparative, i.e., multi-line, phase plots of the  $X_i$  probability and  $G_i$  payoff spaces, respectively, with *exogenous* parameters  $\beta_i = 4, 5, 6, d_i = 0.5$  and  $k_i = 1.2, 1.4, 1.6, i = 1, 2$ . The  $X_i$  phase plot on the upper right of Fig. 7 shows two elliptic centers,  $K_1$  and  $K_2$ , above and below the  $X_1 = X_2$  diagonal, around which the games of 'locked-in' players oscillate perpetually.

Figure 7 Phase plots of the  $X_i$  probability space, with exogenous parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2





Figure 8 Phase plots of the  $G_i$  payoff and loss space, with *exogenous* parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2

Also marked on the upper-right, time-independent  $G_i$  payoff phase space (Fig. 8), the two hyperbolic saddles of the stable  $U_1$  and unstable  $U_2$  manifolds separate the  $K_1$  and  $K_2$  regions from the rest of the phase space. The  $G_i$  functions estimate instantaneous payoff, so each player's collegiality depends on the rate at which payoff changes as a result of collaboration. The oscillating  $K_1$  and  $K_2$ periodic attractors show how games with *exogenous* parameters can result in perpetual, never-ending conflicts. Outside the oscillating  $K_1$  and  $K_2$  regimes, however, player tactics that begin at the  $S_4$  state of discord and lack of collegiality can lead to the  $S_1$  state of full collaboration (Fig. 1a and b).

Turning to the time domain of Fig. 9, a pertinent goal of the system dynamics modeling process is to create insight through coherent and dynamically correct explanations of how influential pieces of system structure give rise to system dynamics. Digest R helps detect the causal pathways that contribute the most to generating the dynamics a selected variable shows. The software first slices the

selected variable's time path or trajectory into discrete phases, corresponding to seven behavior patterns through time (legend caption, Fig. 9). Once the selected variable's time trajectory has been cut into distinct phases, PPM determines which structure is most influential in generating the selected variable dynamics within each phase. As one or more causal pathways combine to form circular feedback loops, combinations of circular pathways can define the most influential or prominent causal structures within each phase (Mojtahedzadeh 2001).

The time-series graph on the top-left panel of Fig. 9 shows the shifting prominent structure and polarity phases of  $X_1$  and  $X_2$ , respectively, in the exogenous, constant parameter model. Each phase of each collaboration probability  $X_i$ , i = 1, 2 is a distinct phase of the simulation time. Within each phase, Digest (B) computes both the slope and the curvature of each  $X_i$  stock from its first and second time derivatives, respectively. The clear, un-shaded phases of the thumbnail icons on the top right of Fig. 9 show balancing (–) growth or decline dynamics. The shaded phases show reinforcing (+) growth or reinforcing decline. The behavior phases of the  $X_1$  and  $X_2$  collaboration probability stocks alternate periodically through time, diametrically opposed yet in perfect syzygy with each other.



Figure 9 Shifting prominent structure and polarity phases of  $X_1$  and  $X_2$ , with *exogenous* parameters

The behavior phases of  $X_1$  and  $X_2$  differ from their shifting prominent structure and polarity phases (top left, Fig. 9). The two lower panels of Fig. 9 (above the legend) show which causal pathways or structures contribute the most to generating the observed dynamic patterns of system behavior. Corresponding to the first phase of  $X_1$ , for example, is the balancing (–) causal pathway or structure #1, the most prominent loop in generating the initial decline of  $X_1$ .

According to Digest (B), structure #1 is the most prominent pathway not only in generating the shifting prominent structure phases 1, 3 and 5 of  $X_1$ , but also in generating phases 1, 3 and 5 of  $X_2$ . This prominent structure is the outer causal loop #3 of Fig. 3. In principle, it is a reinforcing loop or positive pathway. According to Digest (B), however, its polarity changes as it takes the role of the most prominent causal structure in generating the dynamics of both  $X_1$  and  $X_2$ .

With  $X_1 = 0.8$  (left axis, Fig. 9) and  $X_2 = 0.2$  (right axis) at time t = 0 (zero) days, both stocks decrease in tandem until t = 4.5 days. But the  $X_1$  stock follows a balancing decline pattern and the  $X_2$  stock shows reinforcing decline dynamics. After that time and until t = 5.75 days, both stocks are in the second phase of Fig. 9.

There, the balancing prominent causal pathway or structure #2 takes over, contributing the most to generating the dynamics of  $X_1$  and  $X_2$ . Interestingly, according to *Digest*® again, this same causal loop structure #2 changes its polarity from negative to positive when it regains prominence in the fourth phase of Fig. 9. After t = 36 days, the same repeated pattern of shifting prominent structure and polarity phases cause the  $X_1$  and  $X_2$  stocks to oscillate forever.

# Endogenous parameter (complete self-reference) model results

The more complex and realistic model of paradoxical self-referential games in business and civil litigation calls for  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2 to depend on the  $X_i$  stocks (Fig. 4 and 5b, and Table 3). In this complete self-reference model, each player considers the other's collegiality or discord completely. Owing to the dependence of the six parameters on  $X_i$ , Fig. 10 shows that the resulting behavior is very different from Fig. 7 and Fig. 8, now showing *dissipative* dynamics with moderate equal gains.

Figure 10 Phase plots of the  $X_i$  and  $G_i$  spaces, with *endogenous* parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2



On the left panel of Fig. 10, practically all initial collegiality and discord tactics lead players to the fixed-point attractor K, a stable node with a rather large basin of attraction. K is on the  $X_1 = X_2$  diagonal. As K gets closer to (1, 1), the two players can enjoy equal and higher payoff. It is worth noting that the two hyperbolic saddle points of the  $U_1$  and  $U_2$  manifolds on Fig. 7 are still present on the left panel of Fig. 10, now outside the unit square. On the right panel of Fig. 10, the  $G_1$  and  $G_2$  payoff functions increase monotonically at first. Near the (0,0) point, both  $G_is$  are negative, representing losses. As the players move K closer to (1, 1), however, the  $G_i$  values become positive, yielding a higher payoff, equal for the two players on the  $G_1=G_2$  diagonal. But if their fixed-point attractor moves above or below the diagonal, it is respectively either the first or the second player who enjoys the highest payoff (see the *asymmetric impartiality model results section*).

A "surprising result" Nicolis et al. (2001, 322) exclaim when they see that almost all their initial collegiality and discord tactics lead players to the fixed-point attractor K (Fig. 10). This response is typical even among seasoned researchers who rely on dynamic and operational thinking, but do not seek insight from system structure to accelerate their circular causality thinking (Richmond 1993). In the analysis of the endogenous parameter model results, Mojtahedzadeh's (2001) *Digest*® software allows exploring how the system structure of circular causal relations might determine the players' actions as they learn by playing their game iteratively.

Back to the time domain (Fig. 11). The behavior phases of  $X_1$  and  $X_2$  (top-right thumbnail icons) differ widely in the endogenous parameter model (Fig. 4 and Table 3). The  $X_1$  stock changes its behavior phases three times before it reaches its fourth, equilibrium phase. Conversely, the  $X_2$  stock changes only once before it enters its second, final equilibrium phase.

With  $X_1 = 0.7$  (left axis, Fig. 11) and  $X_2 = 0.3$  (right axis) at time t = 0 days, both stocks now *increase* in tandem. The first player's collegiality probability  $X_1$  follows a reinforcing growth pattern until t = 2.5 days and then switches into balancing growth dynamics (refer to the legend caption of Fig. 9). The second player responds with an also rising collaboration probability  $X_2$ , which shows a reinforcing growth pattern too. And s/he too switches into balancing growth dynamics but not until t = 9.5 days. Both stocks show *balancing* dynamics in their final, equilibrium behavior phase, phase 4 for player one and phase 2 for player two, respectively. But the  $X_1$  stock follows a balancing *decline* behavior pattern, whereas the  $X_2$  stock shows balancing growth dynamics.

The time-series graph on the top left of Fig. 11 shows the shifting prominent structure phases of  $X_1$  and  $X_2$ , respectively, for the model with endogenous parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2 (Fig. 4 and 5b, and Table 3). The two lower panels of Fig. 11 show which causal pathways of system structure contribute the most to the observed dynamic patterns of the endogenous parameter model.

Corresponding to the first phase of behavior the  $X_1$  stock shows are the two reinforcing (+) prominent causal pathways or structures #3 and #4. These two loops are most prominent in generating the initial reinforcing growth of  $X_1$ . The same causal pathways #3 and #4 are also most prominent in generating the shifting prominent structure phases 1 and 5 of  $X_2$ . Although dominated by these two *reinforcing* causal structures in its fifth phase, the  $X_2$  stock persistently shows *balancing* growth dynamics.

The first three phases of  $X_1$  and  $X_2$  are identical in terms of their timing, up to time t = 9.5 days. Thereafter, the fourth phase of  $X_1$  ends at t = 26.75 days, while the fourth phase of  $X_2$  lasts until t = 27.25 days. Then the phase times shift again so that the  $X_1$  and  $X_2$  stocks end their fifth phase concurrently at t = 29.25 days. Which makes their sixth, final equilibrium phases coincide time wise.



Figure 11 Shifting  $X_i$  prominent structure phases with *endogenous* parameters  $\beta_i$ ,  $d_i$  and  $k_i$ , i = 1, 2

In the middle of the large time-series graph of Fig. 11, the small block arrow shows where the  $X_1$  and  $X_2$  phases break off. Without strong evidence to the contrary, this phase break off might well be what causes the paradoxical, completely self-referential game model with endogenous parameters to end up in a fixed-point attractor. Although rather small, the shifting prominent structure phase break off might be sufficient to disrupt the periodic attractor of the exogenous parameter model and, thereby, to help the players reach the fixed, optimum optimorum, equilibrium point *K* of Fig. 10.

This implies extra leverage in encouraging collegiality and collaboration in business and civil litigation. One way that Nicolis et al. (2001, 325) suggest is to decrease the tempting payoff and/or to increase loss due to discord, by making the exogenous  $\beta_0$  and  $k_0$  parameters (Eq. 31 and Eq. 32, Table 3) smaller and larger, respectively. But it might also be possible for litigants to reach the stable equilibrium of a win-win victory if they can find a way to simply break off the identical time wise phases of a perpetual, never-ending conflict (Fig. 9).

# Symmetric impartiality model results

A third way is to help players become increasingly and symmetrically unbiased toward each other's collegiality or propensity to collaborate and initial discord tactics. The impartiality or indifference parameter p ( $0 \le p \le 1$ ) of Fig. 6a and Eq. 37 (Table 4) allows making it so. As p decreases on Fig. 12, each player becomes symmetrically more impartial toward the other, free to collaborate collegially, without undue bias and preconceived notions.



Figure 12 Phase plots of the  $X_i$  space, i = 1, 2 for the symmetric impartiality model ( $\beta_0 = 4, k_0 = 1.2$ )

As *p* decreases on Fig. 12, under this model of symmetric impartiality (Fig. 6a and Table 4), the fixed-point attractor *K* moves up the  $X_1 = X_2$  diagonal toward (1,1). Likewise, the players' equal (symmetric) payoff moves up too (Fig. 13), as they equally discount each other's propensity to collaborate. Figure 14 shows exactly how the declining *p* affects both players' collegiality probabilities  $X_i$ , and the percentage and cumulative percentage changes in their symmetric payoff function  $G_i$ , i = 1, 2. Again, at p = 1, the results revert to those from the endogenous parameters model (Fig. 10), but including them here makes the results easy to compare.



Figure 13 Phase plots of the  $G_i$  space, i = 1, 2 for the symmetric impartiality model ( $\beta_0 = 4, k_0 = 1.2$ )

Figure 14 Effects of p on  $X_i$ ,  $G_i$ , i = 1, 2 and percentage gains from the symmetric impartiality model



Specifically, as p declines from 1 to 0.7 on the left panel of Fig. 14, the two players' fixed-point collegiality attractor moves from K = (0.6844, 0.6844) to K = (0.9951, 0.9951), well into the  $S_1$  state of full collaboration (Fig. 1a and b). This is a 40 percent cumulative gain in the players' propensity to collaborate. Similarly, as p decreases along the same interval on the right panel of Fig. 14, the players' symmetric payoff functions move from  $G_1 = G_2 = 0.15$  to  $G_1 = G_2 = 0.99$ . Owed to each player's collegiality and equal impartiality toward the other's propensity to collaborate, this  $G_i$  shift represents an amazing win-win scenario of a 263 percent cumulative gain in the players' equal payoff.

Yet, how does this astounding improvement come about? What causes it? Why?

In the time domain of Fig. 15, the behavior phases of  $X_1$  and  $X_2$  do not look much different from the thumbnail icons on the top right of Fig. 11. Initially, both stocks show a reinforcing growth pattern, followed by balancing growth dynamics, which  $X_2$  sustains until the fixed-point attractor *K* has absorbed all dynamics, leaving both collegiality stocks in a stable, negative feedback state.

Figure 15 Shifting prominent structure phases of  $X_1$  and  $X_2$  with symmetric impartiality



The shifting prominent structure phases of Fig. 15 tell, however, an entirely different story. Time wise, only the first prominent structure phase of Fig. 15 is identical for the two players' collegiality stocks. After time t = 4 days, the third phase of  $X_1$  and the second phase of  $X_2$  meet again at t = 12.5 days. But while the fourth phase of  $X_1$  ends at t = 25.5 days, the third phase of  $X_2$  lasts until t = 31.75 days. Corresponding to their first, common shifting prominent structure phase is the reinforcing (+) structure #3, a causal pathway most prominent in generating the initial reinforcing growth of both  $X_1$  and  $X_2$ .

After t = 4 days, reinforcing (+) loop #7 becomes prominent in generating the behavior of both stocks, but the prominent causal path via which it affects  $X_1$  changes after t = 4.5 days. Hence,  $X_1$  enters a balancing growth era after t = 4.5 days, while  $X_2$  continues to ascend on its reinforcing growth trajectory until t = 12.5 days. Subsequently, after t = 12.5 days, the  $X_1$  stock embarks on its fourth prominent structure phase, while  $X_2$  is just beginning its third phase.

In the middle of the large time-series graph of Fig. 15, another small block arrow again shows where the  $X_1$  and  $X_2$  phases break off. Without strong evidence to the contrary, once more, this phase break off might well be what causes this paradoxical, completely self-referential game model with endogenous parameters and symmetric impartiality to end up in a fixed-point attractor.

Although still small, the shifting prominent structure phase break off might be sufficient enough to move the system widely through its state space, thereby helping the players reach the fixed-point attractor *K* of Fig. 12. According to *cybernetics*, the science of communication and control, and *thermodynamics*, the more widely a system moves through its state space, the faster it ends up in an attractor (Prigogine and Strengers 1984, Zhabotinsky 1973).

A "surprising result" Nicolis et al. exclaim again (2001, 325) when they see that players caught in this paradoxical, completely self-referential game with endogenous parameters and symmetric impartiality can eventually conclude at the  $S_1$  stage of full collaboration, as *K* moves up the diagonal with decreasing *p* (Fig. 12). Once more, this reaction is typical among researchers deprived of the accelerated circular causality thinking (Richmond 1993) that Mojtahedzadeh's pathway participation metric (1996) provides in his *Digest*® software (2001).

## Asymmetric impartiality model results

The results so far have been from game model variants with symmetric structures (Fig. 2a, Fig. 4 and Fig. 6a). The dynamics would have been invariant if the two players were to swap positions. But the endogenous parameter q ( $0 \le q ) of Fig. 6b and Eq. 40 (Table 5) now helps assess what would happen if one player were to account less for the other's collegiality. Figure 16 shows the phase plots of the <math>X_i$  space and Fig. 17 the phase plots of the  $G_i$  space, i = 1, 2, respectively, from the *asymmetric* impartiality model.

As the  $X_1X_2$  phase plot on the lower-right panel of Fig. 16 shows (where p = 1 and q = 0.95), the game's *a*symmetry is clear. Both p and q decrease on Fig. 16, following a 'Z' pattern in reverse. As they do, under this *a*symmetric impartiality model (Fig. 6b and Table 5), the fixed-point attractor K climbs up toward (1, 1) and yet consistently stays below the  $X_1 = X_2$  diagonal of the unit square.

Likewise, as p and q decrease on Fig. 17, the players' *un*equal (*asymmetric*) payoff moves up too. But the payoff of the second player is consistently higher than the payoff of the first, as the second player accounts less for the other's collegiality or lack of it. Figure 18 shows exactly how the declining p and q affect each player's collegiality probability  $X_i$ , and the percentage and cumulative percentage changes in their *asymmetric* payoff functions  $G_i$ , i = 1, 2. Owed to the game's *asymmetry*, at p = 1, the dynamics now does not revert to the endogenous parameters model results of Fig. 10.

Specifically, as *p* declines from 1 to 0.7 and *q* from 0.95 to 0.665, on the top panel of Fig. 18, the fixed-point attractor *K* moves from K = (0.7767, 0.5955) to K = (1.000, 0.9490), well into the  $S_1$  state of full collaboration (Fig. 1a and b). This is only a 27 percent cumulative gain in the first player's propensity to collaborate, but a 51 percent cumulative gain the second player's collegiality. Similarly, on the lower panel of Fig. 18, the two players' *asymmetric* payoff functions move from  $G_1 = 0.15$  to  $G_1 = 1.07$  for the first player and from  $G_2 = 0.52$  to  $G_2 = 1.24$  for the second player. Owed to both players' collegiality but *un*equal impartiality toward each other's propensity to collaborate, the cumulative shift is 281 percent in  $G_1$  and 108 percent in  $G_2$ , an amazing win-win scenario compared to the perpetual, never-ending conflicts of the exogenous parameter model.



Figure 16 Phase plots of the  $X_i$  space, i = 1, 2 for the *asymmetric* impartiality model ( $\beta_0 = 4, k_0 = 1.2$ )

Figure 17 Phase plots of the  $G_i$  space, i = 1, 2 for the *asymmetric* impartiality model ( $\beta_0 = 4, k_0 = 1.2$ )





Figure 18 Effects of p on  $X_i$ ,  $G_i$ , i = 1, 2 and percentage gains from the *asymmetric* impartiality model

These results' immediate implication is that impartiality pays. Namely following one's own tendencies toward collegiality and collaboration pays more than paying too much attention to an opponent's propensity for collegiality or to the lack of it. Had the first player played more impartially toward the second, then the first player's payoff would have been higher than the second player's.

But how does the *asymmetric* structure of the last impartiality model cause these results? How can *asymmetric* impartiality ensure that paradoxical self-referential games with endogenous payoff, prior discord and loss parameters can end at the S1 state of full collaboration?

In the time domain of Fig. 19, one last time, the behavior phases of  $X_1$  and  $X_2$  look very similar to the thumbnail icons on the top right of Fig. 11 and Fig. 15. The first, reinforcing growth behavior phase of  $X_1$  does last longer, however, as one moves from Fig. 11 to Fig. 15 to Fig. 19. As a result, within the endogenous parameter game models, both players' collaboration probabilities increase as they move from complete self-reference (p = 1) to symmetric impartiality (p = 0.8) to *a*symmetric impartiality (p = 0.8, q = 0.76). A balancing growth pattern follows the two stocks' initial reinforcing growth dynamics. All three game models end when the fixed-point attractor *K* has absorbed all dynamics, leaving the system in a stable, negative feedback state.



Figure 19 Shifting prominent structure phases of  $X_1$  and  $X_2$  with asymmetric impartiality

Time wise again, only the first prominent structure phase of Fig. 19 is identical for the two stocks. After time t = 3.75 days, the third phase of  $X_1$  and the second phase of  $X_2$  meet again at t = 12.25 days. The fourth phase of  $X_1$  now ends at t = 25.25 days, but the third phase of  $X_2$  lasts until t = 29.75 days. Once more, corresponding to their first, common shifting prominent structure phase is reinforcing (+) pathway #3, reinforcing the initial growth of both  $X_1$  and  $X_2$ .

After t = 3.75 days, reinforcing (+) loop #7 again becomes prominent in generating the behavior of both stocks, but the prominent causal path via which it affects  $X_1$  changes after t = 6 days. So  $X_1$  enters a balancing growth era after t = 6 days, but  $X_2$  continues to ascend on its reinforcing growth trajectory until t = 12.25 days. After t = 12.5 days,  $X_1$  embarks on its fourth prominent structure phase, while the second player's stock  $X_2$  is just beginning its third phase.

The small block arrow is unnecessary this time. Between t = 3.75 and t = 6 days, the prominent structure phase break off on the top left of Fig. 19 is so wide, it is hard to miss. Without strong evidence to the contrary, once more, again this phase break off might well be what gives the *asymmetric* impartiality game model ample help to end up in the fixed-point attractor *K*.

And as on Fig. 15, on Fig. 19 too, the second prominent structure phase break off is even wider than the first. After time t = 12.25, the balancing (–) prominent structure #9 tapers off both stocks' growth. This causal pathway stays dominant for  $X_1$  until t = 25.25 days, and even longer for  $X_2$ , until

t = 29.75 days. So it is between t = 25.25 and t = 29.75 days that the second prominent structure phase break off occurs, precisely when balancing (–) structure #5 becomes most prominent in taming both stocks, and thereby enabling the fixed-point attractor *K* to absorb all their dynamics.

## Discussion and conclusion

Nothing is random in life. Although it pervades all business processes and systems, "randomness is a measure of our ignorance", argues Sterman (2000, p. 127). Georgantzas and Orsini (2003) concur.

Purely deterministic, this paper's system dynamics game models help explore non-constant sum, paradoxical self-referential games between two players, who enter a conflict situation trying to maximize their respective potential payoffs. While playing rationally according to set rules, both players can concurrently win or lose in such games, depending on whether they choose collegiality and collaboration or opt for discord tactics.

Four system dynamics game models help explore the dynamic repercussions of these two means of conflict resolution in business and civil litigation. The models and associated computer simulation results might apply even in situations where organizational control parameters and collegiality probabilities depend predominantly on intrinsic motivation rather than on extrinsic rewards. Early formulations of such games used exogenous constant parameters for the payoff  $\beta_i$  and loss  $k_i$  coefficients linked to discord, and a fixed prior discord parameter  $d_i$  (Nicolis 1986). Later, however, Nicolis at al. (2001) made their models more realistic by treating these parameters endogenously, so that  $k_i$  and  $d_i$  increase together as  $X_i$  increases and  $\beta_i$  decrease in inverse proportion to increasing collegiality and collaboration (i = 1, 2). Nicolis et al. see

these parameters as the 'environment' surrounding the contestants... influencing [their tactics], but is in turn plastically modified by them... 'natural selection' is not a one-way process; it is a feedback loop between the environment and the organisms involved (Nicolis et al. 2001, p. 330).

Although Nicolis at al. err slightly in counting the number of loops involved, by 207 loops to be exact, the results of this system dynamics interpretation of their models support their enlightening results. If collegiality equally affects both players' tendency to collaborate, for example, the game ends at fixed collaboration probabilities with moderate payoffs for both instead of ending at a state of full collaboration with maximum payoffs. But the more collegial both players are and the more they disregard each other's tendency to collaborate, the more their initial conflict is likely to end in full collaboration. In the long term, those who choose to collaborate regardless of the others' attitudes can see their payoff increase drastically (lower panel, Fig. 18). These results support both the collaborative law proponents and Deming's (2000) new climate and win-win predicament.

But if Deming and his predicament can find their place in the traditional civil-litigation battlefield and combats, then why do business, government and other nonprofit organizations still resist them? Deming's win-win proposition does not advocate socialism, typically an attempt to redistribute wealth through taxation and social programs. Deming is not talking about redistribution of wealth, but rather about principles and methods that can increase the wealth of all concerned...

Poise and impartiality pay because the less attention a player pays to other's collegiality, the more that player gains as the initial conflict approaches a fixed state of mutual collegiality and

collaboration. Even if two players reach a stalemate with fixed discord tactics and limited payoffs, they can still make progress and see their payoffs increase if each player follows a collegiality policy independently of the other's willingness to reciprocate or not.

One way to promote collegiality and collaboration in business and civil litigation is to decrease the tempting payoff and/or to increase loss due to discord, by making the exogenous  $\beta_0$  and  $k_0$ parameters (Eqs 31 and 32, Table 3) smaller and larger, respectively. Yet a third possibility would entail for at least one of the litigants to find a way to simply break off the identical time wise phases of a perpetual, never-ending conflict (Fig. 9), to reach the stable equilibrium of a win-win triumph (Fig. 10 through Fig. 19). Naturally, doing so will take *trust*, with all its complex loops between it, the economic and political fabric of society, and the individuals who constitute that society (Good 2000).

It is Digest (Mojtahedzadeh 2001), with its analysis of shifting prominent structure and polarity phases that has helped reveal this third possibility, as a means to promote collegiality and collaboration in business, civil litigation and, perhaps, even in today's multitude of international conflicts. Digest (R) offers a novel mode for understanding and explaining what would normally require dominant loop (Richardson 1995) and eigenvalue analyses (Forrester 1983). Qualitatively, using Mojtahedzadeh's (1996) pathway participation metric implemented in Digest (R) feels much akin to simulation than to eigenvalue analysis. Armed with PPM, however, Digest (R) delivers results equivalent in rigor to eigenvalue analysis, but with the finesse of computer simulation.

To abolish the shifting loop polarity phases of Fig. 9, one could easily decompose the equations of motion on Table 2a (Eq. 3 and Eq. 4). But doing so would increase the number of feedback loops of the exogenous parameter model (Fig. 2a and Fig. 3) from three to 19 loops per  $X_i$ , i = 1, 2 and lead to a new causal structure, unlike the one Nicolis (1986) and Nicolis at al. (2001) derived.

It would be both premature and unproductive to draw broad generalizations based on this paper's limited findings. Although tempting to use its results, some conflicts may provide justification but others contradiction. Business and civil litigation conflicts often involve multiple players and stakeholder groups, rendering them far too complex to explain with this paper's tiny system dynamics game models. If valuable, the results merely suggest possible future research in modeling paradoxical games between two or among multiple players. One possible extension is, for example, to treat the already endogenous  $d_i$  parameters of prior discord as state variables, like the  $X_i$ s. As Nicolis at al. (2001) point out, that might entail adding at least two more stocks and flows to the model, will render the phase space multidimensional and add new exciting features to these models, such as the possibility of chaotic attractors.

Meanwhile, unaware that only full collaboration can maximize payoff, business managers and civil litigation lawyers alike continue to choose between collegiality and discord tactics hoping to see their payoff rise. In response, following Mr. Webb's daring lead, collaborative law is becoming the practice of law using a multidisciplinary approach to problem solving that deems adversarial techniques and tactics unnecessary (Bushfield 2002). All parties to a dispute and their attorneys agree to resolve the dispute without going to court. The process is characterized by a strong commitment of collegiality founded on an atmosphere of honesty, cooperation, integrity and professionalism geared toward the future well being of all concerned. Where positions differ, participants create proposals that meet the fundamental needs of both parties and they will compromise if they must to settle all issues in a collegial manner.

# References

- Arnold T. 2000. Collaborative dispute resolution: an idea whose time has come? American Law Institute (ALI) - American Bar Association (ABA) Continuing Legal Education, ALI-ABA Course of Study, SF16(Oct): 379.
- Ashford AC. 2001. Unexpected behaviors in higher-order positive feedback loops (D-4455-2). In *Road* Maps 7: A Guide to Learning System Dynamics. System Dynamics in Education Project, MIT: Cambridge, MA.
- Bushfield N. 2002. History and development of collaborative law. Available online: www.iahl.org/articles/04 History and Development.htm.
- Cooter RD and Rubinfeld DL. 1989. Economic analysis of legal disputes and their resolution. *Journal* of *Economic Literature* **27**: 1067.
- Courcoubetis C. and Yannakakis M. 1988. Verifying temporal properties of finite state probabilistic programs. In *Proceedings of the IEEE Conference on Decision and Control*, pp. 338-345.
- Crocker C and Hampson FO (Eds). 1996. *Managing Global Chaos: Sources of the Response to International Conflict.* US Institute of Peace Press: Washington, DC.
- Deming WE. 2000. *The New Economics for Industry, Government, Education* (2e). MIT Press: Cambridge, MA. Originally published in 1993 by MIT's Center for Advanced Engineering Study (CAES): Cambridge, MA.
- Deutsch M and Krauss RM. 1960. The effect of threat on interpersonal bargaining. *Journal of Abnormal and Social Psychology* **61**: 181-189.
- Eberlein RL. 2002. Vensim® PLE Software (5.2a). Ventana Systems, Inc.: Harvard, MA.
- Fisher R, Ury W and Patton B. 1991. *Getting to Yes: Negotiating Agreement Without Giving In* (2nd Edition). Penguin Group: New York, NY.
- Forrester JW. 2003. Dynamic models of economic systems and industrial organizations. *System Dynamics Review* **19**(4): 331-345.
- Forrester N. 1983. Eigenvalue analysis of dominant feedback loops. In *Plenary Session Papers Proceedings of the 1st International System Dynamics Society Conference*, Paris, France: 178-202.
- Georgantzas NC and Orsini JN. 2003. Tampering dynamics. In *Proceedings of the 21st International System Dynamics Society Conference*, 20-24 July, New York City, NY.
- Gershon ES, Belmaker RH, Kety SS and Rosenbaum M. 1977. The Impact of Biology in Modern Psychiatry. Plenum: New York, NY.
- Good D. 2000. Individuals, interpersonal relations and trust. In Gambetta D (Ed.) *Trust: Making and Breaking Cooperative Relations*. Department of Sociology, University of Oxford: Oxford, UK, pp. 31-48.
- Gould JP. 1973. The economics of legal conflicts. Journal of Legal Studies 2: 279.
- Hansson H and Jonsson B. 1994. A logic for reasoning about time and reliability. *Formal Aspects of Computing* **6**: 512-535.
- Hill OW. 1976. Modern Trends in Psychosomatic Medicine (Vol. 3). Butterworth: London, UK.
- Landes WM. 1971. An economic analysis of the courts. *Journal of Law & Economics* 14: 61.
- McArdle E. 2004. From ballistic to holistic. The Boston Globe (Jan. 11).

- Mojtahedzadeh MT. 1996. A Path Taken: Computer-Assisted Heuristics for Understanding Dynamic Systems. Ph.D. Dissertation. Rockefeller College of Public Affairs and Policy, SUNY: Albany, NY.
- Mojtahedzadeh MT. 2001. *Digest* (B): A new tool for creating insightful system stories. In Proceedings of the 19th International System Dynamics Society Conference, July 23-27, Atlanta, GA.
- Morrison JB. 2001. Limits to the pace of learning in participatory process improvement. In *Proceedings of the 19th International System Dynamics Society Conference*, Atlanta, GA.
- Morrison JB. 2002. The right shock to initiate change: a sensemaking perspective. In *Best Paper Proceedings of the Academy of Management*, Denver, CO.
- Nicolis JS, Bountis T and Togias K. 2001. The dynamics of self-referential paradoxical games. *Dynamical Systems* **16**(4): 319–332.
- Nicolis JS. 1986. *Dynamics of Hierarchical Systems: An Evolutionary Approach*. Springer-Verlag: Berlin, Germany.
- OQPF Roundtable. 2000. Deming's Point Seven: Adopt and Institute Leadership A Commentary on Deming's Fourteen Points for Management. The Ohio Quality and Productivity Forum (OQPF), PO Box 17754, Covington, KY 41017-0754.
- Posner RA. 1973. An economic approach to legal procedure and judicial administration. *Journal of Legal Studies* **2**: 399.
- Priest GL and Klein B. 1984. The selection of disputes for litigation. *Journal of Legal Studies* 13:1.
- Prigogine I and Strengers I. 1984. Order Out of Chaos. Bantam Books: New York, NY.
- Rachlinski JJ. 1996. Gains, losses and the psychology of litigation. *Southern California Law Review* (Nov).
- Rapoport A. 1966. *Two-Person Game Theory: The Essential Ideas*. University of Michigan Press: Ann Arbor, MI.
- Repenning NP. 2003. Selling system dynamics to (other) social scientists. *System Dynamics Review* **19**(4): 303-327.
- Richardson GP. 1995. Loop polarity, loop prominence, and the concept of dominant polarity. *System Dynamics Review* **11**(1): 67-88.
- Richmond B. 1993. Systems thinking: critical thinking skills for the 1990s and beyond. System Dynamics Review **9**(2): 113-133
- Richmond B et al. 2004. *iThink* <sup>®</sup> Software (8.1). iSee Systems<sup>™</sup>: Lebanon, NH.
- Ross, S. 1983. Stochastic Processes. Wiley: New York, NY.
- Shavell S. 1982. The social versus the private incentive to bring suit in a costly legal system. *Journal of Legal Studies* **11**: 333.
- Sterman JD. 2000. Business Dynamics: Systems Thinking and Modeling for a Complex World. Irwin McGraw-Hill: Boston, MA.
- Swingle PG (Ed). 1970. The Structure of Conflict. Academic Press: New York, NY.
- Watzlawick P, Beavin JH and Jackson DD. 1967. *Pragmatics of Human Communication*. Norton, New York, NY.
- Wolf S and Berle BB. 1976. The Biology of the Schizophrenic Process. Plenum: New York, NY.
- Zhabotinsky AM. 1973. Autowave processes in a distributed chemical system. *Journal of Theoretical Biology* **40**: 45-61.