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Modeling and Simulation of Information Flow: A Study of Infodynamic Quantities

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*Abstract***:** - Research shows that an analytical solution of information velocity is intractable but metrics that support understanding the factors that affect information flow can be useful. This paper describes an agent-based model for information flow that explores physical analogs to the metric's causal measures. Interactions and exchanges are modeled as physical properties. Information, its suppliers, and consumers are treated as agent particles. Visibility of information and need are treated as attraction. The barriers to communication as well as the perception of cultural risk are treated as repulsive forces that oppose information exchange. The amount of human-to-human communication is modeled as the maximum distance beyond which information cannot be exchanged (e.g. closeness). The behavior of the particles and system as a whole are discussed vis-à-vis physical properties such as particles in a fluid, momentum, velocity, force, and temperature. Infodynamic and analogs of thermodynamic and other physical quantities associated with these processes are explored. These comparisons may enable a method to combine the various information measures into one or two equations using conceptual analogs from the physical domain with possible applications to improve information flow in command centers.

Keywords: **-** Assessment tools and metrics, C^2 concepts and theory, decision model, decision support, employee empowerment, entropy, infodynamics, information annealing, information flow, information theory, uncertainty.

1. Introduction

Each day in our organizations, each employee makes decisions, some small, some large. What happens to a given decision? Where does it go? Perhaps someone else in the organization is awaiting the decision or someone needs to know of that decision but isn't aware of it. What are the obstacles to that decision reaching the people who need it? What makes people want to share the decision and how much time do we waste trying to communicate and understand the decision? What affects the speed of the individual decision process and the sharing of that decision with others?

These and similar questions are the subject of research exploring the development of metrics for information flow and decision making. The purpose of this paper is to report a way to increase our understanding of information flow in the decision process. Information flow can be modeled as a series of interactions analogous to the interaction of particles, such as atoms or molecules in various states of matter, such as gas, liquid, or solid. The concepts of temperature, pressure, intermolecular forces, and annealing can be applied to information flow and the model can be tested using an agent-based modeling program. Although the research is still ongoing, this model suggests that a broad, general metric for information flow in organizations can simulate the way the members of the organization handle confidence and its inverse, uncertainty.

This paper, which is the sixth in the series of papers on infodynamcs, treats knowledge and decisions in much the same way because of the feedback loop between knowledge and decisions. Decisions are a form of knowledge that results from the aggregation, fusion, and analysis of facts, assumed facts or other forms of information. The decisions themselves become knowledge for others further down the chain of command. Knowledge is information arranged as a higher aggregation of related facts or data that has attained a level of complexity beyond that of traditional transactional data [3]. Knowledge can be expressed as declarative statements or probabilistic networks. Much of the "every-day" input that we encounter is a collection of estimates or assessments that other individuals have made. Each assessment is a decision and the collection of those decisions increases our knowledge. Knowledge of our organization is based on the past and present decisions of our employees.

Information flow is related to entropy and power [12]. Although a practical and mathematically closed-form solution for information flow in terms of observable data proved intractable [12], the comparison of poor information flow to low confidence and high entropy suggests that a physical model might be worth exploring using modeling and simulation. The branch of information theory in which physical thermodynamic analogy is used to explore the behavior of information systems is called Infodynamics [5]. This paper contributes new insight in the exploration of this analogy to study information exchange using modeling and simulation. This paper describes the model and the status of our research to this point.

The paper is organized as follow. Section 2 explains the key causal components of information flow and the physical equivalents in the decision model. In section 3 we consider the effect of factors that promote or inhibit information flow. Section 4 describes the behavior of aggregates of particles. Section 5 describes some preliminary results. In Section 6, we discuss ongoing and future research, including model enhancements and a suggestion that information annealing could be used to model information flow. Section 7, concludes the paper with a brief summary.

2. Causal Measures and Physical Equivalents

Six causal measures are suggested as key contributors for affecting information flow [12]. Each of these causal measures is discussed below with its physical equivalent in the information-flow model.

<u>Visibility of Information (Vi)</u>

The more "visible" the information, the more likely it will be seen by those who need it. Visibility can be improved in a variety of ways, such as by posting on a website, by increasing the clarity of the writing, or by providing the content in a machine-understandable format. When information is visible, those who need it can find it more efficiently.

In this model, one kind of particle represents the information, *I*, and another kind of particle representing the decision-maker who needs the information, *D*. Thus, a collection of particles, *I* and *D*, can be modeled like a gas mixture where the various species, I and D interact with each other in the form of collisions.

During a molecular collision in a fluid, such as a gas or liquid, both the attractive and repulsive forces between the molecules involved in the collision determine not only how the collisions change the physical properties (e.g. instantaneous configuration, orientation, velocity, momentum, various quantum states) and sometimes the chemical properties (e.g. electronic state, dissociation, reaction products) of the molecules involved in the collision, but also contribute to observed properties of the bulk mixture, such as boiling point, melting point, and pressure. Here, we model *I* and *D* as components in a fluid of particles that interact by collisions. The attractive forces in the interaction allow *D* to move toward *I* to the extent *I* is more visible. Obstacles to the interaction of *I* and *D* are like the repulsive forces in fluid mixtures.

Without any visibility, the particles *D* and *I* will move about randomly and an exchange will occur only if they collide with each other. They cannot attract each other from a distance. This is similar to an ideal gas, which is modeled as a collection of point particles that do not interact with each other, i.e. no intermolecular forces.

Gathering around the water cooler or at weekly meetings is one way to improve the likelihood of encountering people and has been a traditional, although inefficient and haphazard, way of finding information. Other ways to increase information flow are available, rather than requiring physical contact and conversations.

<u>Visibility of the Need (Vn)</u>

Similarly, information flow in terms of information exchange will improve if the *need* for the information is visible. If I have information and I see that you need it, information exchange becomes more likely. Conversely, if your need for the information is invisible, I might not know that you need it and you might not discover that I have the information you need.

In terms of the decision maker who needs the information, *D*, and the person who has the information, *I*, a physical model of this causal measure suggests that *I* will approach *D* to the extent *D's* need is visible. The more visible the need, the more likely *I* will move toward *D*, like particles of opposite charge attracting each other.

<u>Empowerment of People (Ep)</u>

When an organization empowers its employees, it treats them and their opinions with respect. (See, for example, [1], [6], [7], and [9].) Its leaders listen to the employees' suggestions and value their involvement in the decision-making process. Empowerment implies a flattening of the traditional hierarchical structure so that employee decisions carry more weight. If employees in our organization are not empowered, they become passive and inhibited as morale declines. They may not have the incentive to try to overcome barriers to information flow. They may not feel comfortable challenging the status quo or opposing conventional opinion or the opinions of their supervisors or colleagues. Such organizations become stale and static in terms of information flow, new ideas are not rewarded, and employees are not promoted for producing new ideas and passing information that differs from those of their supervisors [11].

The physical analog to empowerment is the mass of the particle representing the employee decision maker. Particles with larger mass are capable of delivering more force and power, as expressed in equations (1) through (3) where F is force, M is mass, A is acceleration, W is work (with units of energy), r is distance, Po is power and t is time.

(1) $F = M A$

(2) $W = F r$

(3) $Po = dW/dt$

The more empowered the employee, the more massive the particle representing that employee decision maker is in the simulation. During a collision, a massive particle is likely to deliver more momentum, thus affecting the state of the particle with which it collides. In any interaction, the more mass in a given particle, the more likely the interaction will involve an exchange (e.g. transfer of momentum or transfer of information.) A more massive particle is more likely to overcome obstacles to exchange.

<u>Barriers to Communication (Bc)</u>

Barriers to communication inhibit information flow. A barrier can be anything that impedes the sharing of information. These barriers include dates after which no information sharing is allowed, or formal requirements for information submission, approval chains or other inhibitors. Whatever merits these barriers may have in performing other functions, they impede, or at least delay, the flow of information.

One way to model this is to consider these barriers as the amount of force needed to enable an exchange. These barriers to information sharing are like the repulsive forces in fluids that keep internuclear distances above a certain minimum value. (The equilibrium internuclear distance is determined by the sum of repulsive and attractive forces.) If the barriers to close approach are higher, the amount of force required to enable an exchange is higher, and more energy is required to induce a successful exchange. In this case, the information barriers are analogous to physical barriers that must be overcome by a greater amount of force, and hence greater energy.

One way to determine how empowered employees are is to estimate how much effort (e.g. power and energy) is necessary for them to communicate ideas successfully. If the effort required is too great, or if their time is filled with other tasks, these factors also will act as barriers to information exchange and the power to overcome them may not be available.

Perception of Risk (Pr)

Employees who perceive significant personal risk to their reputations, performance ratings, or promotion opportunities by sharing information are unlikely to share. Moreover, decision makers and support personnel alike also perceive a risk from accepting information that they think may be irrelevant, incorrect, incomplete, or otherwise useless. The greater the perception of risk, the less likely will be the desire of the person with the information to share despite other factors. Pr in an information-exchange situation is like the pressure, P, in a gas.

This analogy is appropriate for two reasons. First, sufficient pressure on a gas mixture can liquefy it and the liquid can separate out into isolated phases, each consisting of nearly pure components. This is analogous to the situation where decision makers do not get the information they need because they are not likely to be near the information sources. (For more detail, see below.) Second, pressure increases the number of collisions per unit time. In a simulation trial, this is a convenient way to model information overlaid. In general, people perceive risk as a form of mental pressure.

In a system of N gas particles that occupy a volume, V, high pressure shrinks the volume of the gas whereas high temperature, T, expands it in a manner described by the ideal gas law, equation (4). K is Boltzmann's constant, the exact value of which is not particularly relevant to this discussion.

(4) $V = NKT/P$

The information analog of (4) that is appropriate for the volume of information exchanges, Ve, is based on an equation for information-system tractability and expressiveness suggested in [5]. This new analog of the ideal gas law that applies to information exchange is given by equation (5) as follows.

(5) $Ve = NKTi/Pr$

In [5], instead of Pr, the information-system expressiveness, E, appears in the denominator. The tractability of an information system, Ti, or (in this case) an information-exchange situation, is analogous to the temperature in a mixture of gas atoms or molecules. That means that all else being held constant, as Pr and Ti work on information exchange in opposite directions like T and P in the gas laws. If Pr is high, a low volume of information exchanges (Ve) will take place, whereas if Ti is high, a high volume of information exchanges will occur.

One way to conceptualize how to model Pr is to relate it to the likelihood of an exchange initiated by the information provider. If Pr is high, the likelihood of information exchange is low and the information provider will need to overcome a personal-risk barrier to make the exchange. If Pr is low, the information provider is more likely to offer the information. Similarly, for decision makers, Pr represents the risk that information is wrong or otherwise useless.

Thus, overall perceived risk (Pr) is an obstacle to effective information exchange. At low degrees of information-exchange tractability, Ti, which models like temperature, (i.e. if information exchange is intractable), Pr will not promote information exchange by increasing the number of collisions between different species. (Collisions or close interactions could promote information exchange and increase information flow.) In the case of information exchange, high Pr is more likely to cause a change in state to a "liquid"-like phase where the two phases are immiscible. Here, Pr separates out the information provider particles, *I*, from the decision-maker particles, *D*, such that they form two immiscible liquid phases like oil on water. Here, the phase containing particles, *I*, is like the water and the decision-maker *D* particles form the oil phase.

Because of adversity to risk at low Ti, particles of similar species tend to group together and insulate themselves from the other group of particles, which also exhibits the same behavior. The only opportunity for information exchange lies along the interface between the phase layers, where a relatively small percentage of the particles of either phase resides. No one wants to interact with anyone in the other "phase" due to the perception of high risk (Pr). People who perceive that they are in a high-risk situation, whether they are providers or decision makers, tend not to provide or obtain information for fear of personal risk or for fear that the information is not useful, respectively.

At higher temperatures, a more information-tractable situation develops [5] Ti increases and the need for information can overcome the perceived risk of providing it. Thus, what was a two-phase system consisting of immiscible liquids at lower Ti (i.e. lower tractability) becomes a one-phase system characterized by the disappearance of the *I-D* phase interface and the miscibility of the two groups of particles, modeled here as phases.

This means that when the overall perceived risk (Pr) is lower, the information-exchange environment becomes more tractable (high Ti). In this case, more information providers can transfer information to decision makers and the decision makers will accept and use the information.

Human-to-Human Communication (Hc)

One of the most common ways for employees in organizations to exchange information is direct human-to-human communication (Hc). Hc can occur either through individual conversations, such as telephone calls, or through meetings, in person, through video teleconferences, or through electronic mail. In general, employees still spend a lot of time in meetings, electronic mail and other forms of direct communication with each other.

These forms of communication are too inefficient for organizations searching for improved information flow. An example of a potential improvement in information flow is a web log (blog), which can share information with everyone in the organization, as opposed to the same information conveyed face-to-face in a meeting or written in a paper submitted up the chain.

The impact of Hc can be modeled like a physical proximity measure. The greater the amount of Hc, the more the information receiver and the information provider must be in close contact to enable an exchange of information. If Hc is very high, the particles must pass within a certain close distance of one another to enable an exchange. If Hc is lower, the exchange can occur at a greater distance and more people can receive the information because the radius of the exchange capability is greater.

Information exchange is not limited to thermodynamic analogs. Other physical properties also can lead to insights in information systems. Thus, Hc behaves like an inverse power law for interaction, proportionality, equation (6) being a general example. Here, P(e) is the probability of information exchange; r is the distance between the interacting particles, Hc is the power law that determines how close particles must be to interact and C is a constant of proportionality. The proportionality sign, α, is like an equals sign (=) but it means that the equation may depend on other variables. However, but the ones mentioned above are the variables relevant in this discussion.

(6) $P(e) \;\alpha\; C / r^{Hc}$

For example, gravitational force acts over a very long distance because its force is proportional to an inverse square law given by equation (7) where F is the force of gravity, G is the gravitational constant, and the M_1 and M_2 are the masses [15]. Equation (7) is known as Newton's law of universal gravitation. We see how the sun, moon and earth interact gravitationally every day to produce the tides. However, the distances between the sun, moon, and earth are much larger than the distances between molecules during interactions in fluids.

(7) $F = G\, M_1 M_2 / r^2$

The higher the exponent of r, the closer the particles must be to feel the strength of the interaction because the force of the effect falls off much more rapidly as the exponent increases. For example, the repulsive forces between molecules can be modeled as $1/r^{12}$ [8], [16]. Forces between nucleons (e.g. protons and neutrons) act over even shorter distances.

Hc behaves like this as well. If Hc is very low, an exchange can be enabled at a potentially great distance to many receivers (all other factors being constant). This is similar to information exchange because reading a blog can be done at a great physical distance to many and doesn't require direct human-to-human communication at close proximity (where Hc is high.)

3. Effect of Information-Flow Components

Effect of Information-Flow Promoters: Vi, Vn and Ep

In the physical equivalent of information exchange, the components discussed above come together in the traditional formula for the force of an interaction. Two particles that are moving directly toward one another will interact with more force than two particles that interact with a sideways or glancing blow. This is due to the fact that velocity (Z), acceleration, momentum (Y), and force are vector quantities and the calculations of their interactions require the resolution of the total quantity into orthogonal components.

Acceleration is the change in velocity over time, where velocity is a vector consisting of speed in a specific direction. Since velocity is a vector, the change in velocity can occur either through a change in speed or a change in direction. The change in direction when two particles interact is maximized when the two particles are headed directly toward each other.

Since the visibility of information (Vi) and visibility of need (Vn) have been modeled as directional components, when they are high, the particles are moving toward each other and the force of the interaction of the particles is greater. Similarly, the momentum, Y, and hence the force, F, of the interaction is greater if the mass of one or both particles is greater, as shown in equations (8) and (9).

(8) $Y = M Z$

(9) $F = dY / dt = M A$

Since we equated empowerment (Ep) to mass, the greater the empowerment, the greater the force of the interaction.

The effect of these three causal measures is combined in equation (9). The greater the Vi, Vn, and Ep, the greater the force of the interaction of the particles. Some particles represent the decision maker who needs the information whereas other particles represent the person with the information. The interaction between the two kinds of particles represents the exchange of information. Therefore, an increase in these causal components will cause a corresponding increase the force of the information exchange.

An alternate way to conceptualize Ep is to think of it as a collision cross section. This tracks with the physical analog. More massive particles in fluids tend to collide with more particles simply because of their larger spatial dimensions.

Effect of Information-Flow Inhibitors: Bc, Pr, and Hc

Consider the other three causal components, Bc, Pr, and Hc, as inversely correlating with information flow.

Barriers to communication (Bc), Perception of risk (Pr) and amount of Human-to-human communications (Hc) all come together in the physical model as inhibitors that work together to make an information exchange more difficult. These are like repulsive forces that keep particles distant from each other. When a decision maker (D) and an Information particle (I) move toward each other, these inhibitors work together to prevent the particles from approaching each other. When *D* and *I* are far away from each other, the likelihood of the exchange being offered is low and the amount of force needed to enable the exchange is high. This can occur either through particles moving directly toward each other or through particles being more massive, i.e. if people are empowered. Either way, to enable an information exchange in an environment where barriers are high, more momentum is required to overcome the repulsive forces of Bc, Pr and Hc.

4. Simulating the Behavior of Aggregates of Particles

Consider the type of behavior enabled in the physical model when many people interact to share or acquire information in an organization. In the physical model, this equates to particles interacting. Assume those particles that have information to share are green and those who need the information (e.g. decision makers without sufficient information) are red, as shown in Figure 1. In this simulation, information flow is like the diffusion of green gas particles. Information exchange is analogous to a "chemical reaction" between the particles that can turn a red particle green. This "reaction" causes a change in the internal structure of the particle that represents a change in the decision maker's state of uncertainty from a high uncertainty to lower one. (See, for example, [5]). The change of color in the simulation signifies this state change.

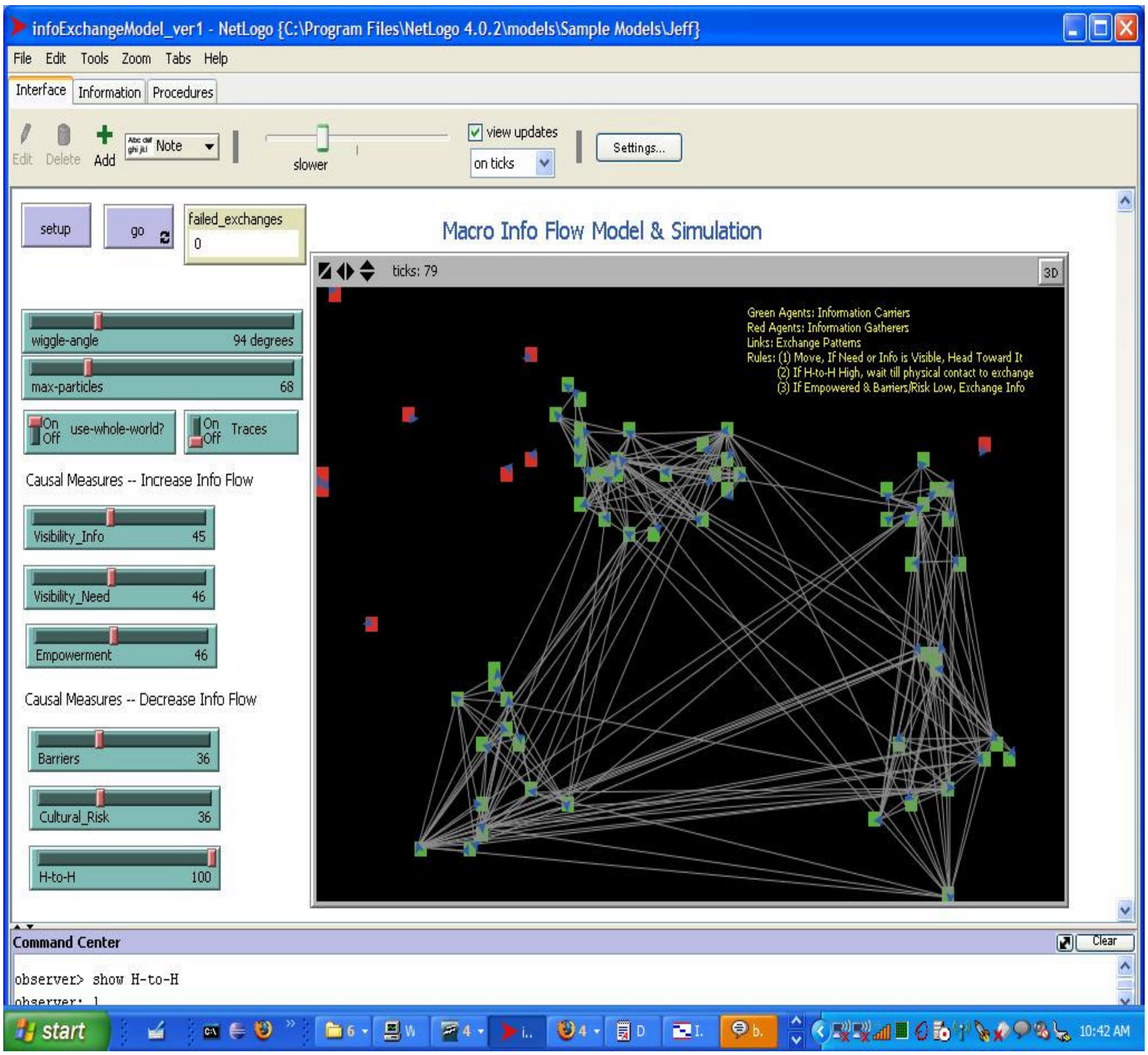

Figure 1. An agent-based model implementation of a physical analog for information flow

The screen shot in Figure 1 shows a "sea" of red (information needy) particles. First, all the red particles are moving at equal speeds in random directions. Next, we introduce a single green (information rich) particle and enable the model to represent an information exchange or transfer of information from a provider to a decision maker by having a red particle turn green whenever an information exchange occurs. Assume that any red particle can receive the information from any green particle, either the original green particle introduced or any other red particle that has turned green as the result of an exchange. The values of the six causal factors can be controlled as independent variables and these values apply equally to all particles.

Figure 1 was produced using a programmable modeling-and-simulation environment called NetLogo [17]. This flexible, efficient, and powerful tool was used successfully in our previous studies. (See, for example, [11].) Net Logo is particularly well suited for modeling complex systems that develop over time. Thus, NetLogo can help the user understand the "swarm" behavior of groups of particles, called "mobile agents."

NetLogo runs on Windows, Mac and Linux. It comes with extensive documentation, tutorials, and a models library that has a large collection of simulations that can be used and modified [17]. During the programming and set-up phase, NetLogo enables the user to create the overall behavior of the model by entering rules for individual agents to follow during the simulation. Each particle is considered an agent. Options available to the user at set-up time include various monitors, a link-shape editor, and a color control that can be used to distinguish the status of agents depending on their initial function and subsequent history of interactions with other agents. For example, an agent that receives a packet of information during an exchange with another agent can be programmed to change its color to show that the information exchange has taken place. Information flow can be modeled and monitored efficiently using this technique.

At run time, the user has a wide variety of options to control the simulation. NetLogo provides an easy and intuitive method to explore the behavior of a simulation under various conditions. In the present simulation, the user can change independent variables systematically and observe the results in subsequent runs of the simulation without having to compile code into an executable file between simulation runs. The user also can control the speed of the simulation.

For example, Figure 1 displays the control panel on the top and left side with eight sliders designed to select values for independent variables. The causal measures described above in Section 2, which increase or decrease the flow of information, each can be varied with its own slider. The relative positions of the sliders provide constant static feedback to the user to indicate the value of each variable and permit comparisons at run time. During this execution phase, the screen shows each particle moving in real time. This provides maximum dynamic feedback to the user regarding the progress of the simulation.

NetLogo has been used to simulate processes in many domains of the natural and social sciences, including but not limited to biology, medicine, physics, chemistry, mathematics, computer science, economics and social psychology [17].

5. Preliminary Results

We observed the model as a whole. If the inhibiting factors are high enough and the promoting factors low enough, the particles will move about, but no information exchange will occur. However, if the promoting factors are high enough and the inhibiting factors low enough, the sea of red particles will become a sea of green particles almost immediately. A more realistic scenario occurs when the operator selects values for the variables that are in between these extremes, which is shown on the left side of Figure 1 with the exception of the H-to-H variable. In this case, the sea of red particles (information deficient) eventually will become green (information rich) over a longer period of time.

6. Discussion of Ongoing and Future Research

An ideal metric of information flow that would apply to the entire organization (generic), would be easy to collect and understand, and measure effects or behavior that correlates well with the definition of information flow. A set of metrics was identified including causal, direct, and effects based [12]. In search for a simple, general but useful measure, a set of 5 survey questions was designed. The work described here suggests an additional approach or question derived from physical modeling.

The current work suggests that information flow can be modeled as a set of interacting particles representing decision makers in need of information as well as information providers and where the interactions are information exchanges which occur (or not) based on a set of individual agent rules equivalent to equation (1). The expected behavior of the system involves a dynamic adjustment when information is injected and then a return to stability after the information is exchanged through the system.

Model Enhancements and Attributes of Particles

This section describes how the attributes of *I* and *D* particles can be modeled to provide a deeper understanding of information flow and exchange. Enhancements to the model need to include factors like deadlines, information requirements, information content, partial information exchange and uncertainty.

Let "n+" represent the amount of useful, current, and applicable information that a given information-provider (*I*) particle contains. The plus sign was selected because "information push" is like a positive pressure.

Let "n-" represent the amount of information a decision-maker particle needs to enable a decision at an acceptably low level of uncertainty. The minus sign was selected to signify "information pull" - a lack of useful information or an "information depression." The larger the "n-", the greater the need for information and the more collisions with *I* particles will be required to turn the *D* particle green.

When multiple collisions with *I* particles are required for a decision to be forthcoming from a *D* particle, the simulation will need to keep track of how many collisions each D particle has had with the *I* particles to be able to tell when a decision can be made. This represents an increase in both the simulation realism and the simulation complexity.

Each decision-maker particle has an associated deadline, t_d, by which the decision must be made regardless of the information available at that time. Similarly, each information-provider particle also has an expiration time, t_e, after which the information becomes stale, irrelevant, wrong, or otherwise useless. Thus n+ declines as a function of time and n- declines as a result of useful information exchanges.

In the simulation, particles interact over a period of time and partial information transfers are allowed. Thus, n- can decline but will not necessarily reach zero before t_d or before the end of the simulation period. If n- reaches zero before $t = t_d$, a decision is made and the red particle will turn green.

If, however, when the $t = t_d$ and n- is still not zero, a decision will be made anyway and the decision will be based on the amount of information that has been received. In this case, the red particle will turn yellow to signify that a decision was made under uncertain circumstances. The confidence measure, Cd, for the decision, d, and the uncertainty, U, with which the decision was made can be calculated according to equations (10) and (11).

(10) $Cd(t) = 1 - U(t)$

(11) $U(t) = n\text{-}\ (t = t_d)\ /\ n\text{-}\ (t = 0)$

Equation (10) models the confidence as the arithmetic inverse of the uncertainty. Uncertainty, U, simply compares the amount of information available for the decision to the amount of information that was originally needed, ignoring any interactions between the information received in successive reductions of n- that could make n- decline faster than linearly.

In equations (10) and (11), confidence level, Cd(t), and uncertainty, U(t), can change during the simulation as information is transferred incrementally from the information-provider particles to the decision-maker particles.

Some data are perishable whereas others persist over a long period of time. As the simulation progresses, the decision-maker particles change the amount of information they need. Deadlines, t_e and t_d, can be selected randomly according to a distribution within reasonable limits, or they can be selected systematically according to the data-duration type and the decision model, respectively.

For example, information-provider particles can be assigned fixed expiration times, t_e, for their data, depending on how often their content can change. Examples of each are given below in Table 1. After initial assignment during the simulation-setup stage, t_e and t_d, remain constant for each particle and for the duration of the simulation.

Table 1. Levels of data persistence

Data-duration type	Example	Typical t_e
Static	Port location	500 years
Semi Static	Ship's OPCON	5 months
Dynamic	Aircraft location	5 minutes

Not all collisions between unlike particles result in information transfer. When the time of the simulation reaches the t_e of an information-provider particle, the effective collision cross section of that particle goes to zero and it will cease to attract any decision-maker particles and no information will transfer. This is how the model depicts the fact the data have become useless for decision making after $t = t_e$. How this state of uselessness is reached depends on the details of the information model.

In the dual-state "cookie-cutter" model, n+ is a constant until $t = t_e$, when n+ = 0. In the linear model expressed in equation (12), n+(t) starts at n_i+ and approaches zero linearly as the simulation time, t, approaches t_e such that when $t = t_e$, n+ = 0.

(12) $$n+(t) = \{- n_i+/ t_e \} \; t + n_i+$$

In more sophisticated information models, n+ can depend on multiple variables, such as time and information reliability, as expressed in factors from the data pedigree, such as source reliability, and the applicability of data-fusion methods. (See, for example [4].)

In reference to the definition of n+ stated above, n+ can decline based on its timeliness or its usefulness. For example, the attraction between the information-provider particles and the decision-maker particles also can depend on whether or not a particular decision-maker particle already has the information that is contained in n+. If the decision-maker already has the information, obtaining redundant information will not constitute an information flow because it will not decrease uncertainty.

Perishable data of the form n+(t) and decision makers, n-(t), with expiration deadlines are analogous to unstable molecules in a chemical mixture. These particles must react before they decompose, or the will not be able to participate in any reaction (other than decomposition).

The limitations in these models include the following observations. Information from various providers is often interdependent but the models are based on the assumption of information independence. One way to model data fusion is to consider three-way, four-way or higher collisions that involve more than two particles colliding and interacting simultaneously. However, this analogy breaks down when you consider that the percentage of multi-body collisions in gases is typically less than one percent, whereas the need for data fusion prior to decision making is much more common than that. Few significant decisions are made after the ingestion of only one datum or fact. Even decisions concerning simple matters usually are based on the fusion and consideration of multiple facts and observations.

Another important point to note in this simulation is its level of granularity. No attempt thus far has been made in this simulation to model the fine structure of the decision-making process as the *D* and *I* particles collide and interact. The effect of collisions on molecular quantum states in fluids is much better characterized from a theoretical [10] and experimental [2] standpoint than the effect of information flow on decision making. Elements of the decision-making process could be included in the model with the aid of a Common Decision Exchange Protocol [13], among other tools and technologies.

The process of imparting fine structure to the decision-making process in the *D* particles is expected to be more complex than the process of specifying the manner in which n+ approaches zero for the *I* particles. This complexity arises out of the fact that information flow and the decision that this flow enables may depend on an unspecified number of variables [5], whereas the accuracy of a data element depends on how far it has departed from its initial value.

One aspect of fine structure is the shape of the particles. Up to this point, we assumed that the particles are isotropic. Introduction of particle anisotropy could enable us to model the amount of information exchanged in a transfer and the effect on the decision maker after the transfer. Assume that the *D* and *I* particles are rods and not spherical, with many of the same rotational properties as linear molecules (See, for example, [2].) For example, to model a collision between two rods, one would have to account for the relative orientation of the particles upon impact. Different relative orientations could signify different amounts of information transfer. The exact function for this information transfer as a function of relative angles is an open research question, the answer to which would depend on which function leads to the most useful model.

Another aspect that could be modeled like molecular dynamics is to allow three-way or higher collisions. Van der Waals dimers are formed during three-way collisions in monomer gases. The use of multi-body collisions involving multiple *I* particles could lead to new ways to model data fusion.

Information Annealing as a Metric for Information Flow

An additional observation is that the dynamic portion of the process increases the entropy of the system. In information theory, entropy expresses the amount of uncertainty in a system. Before new information arrives, the number of choices facing decision makers may be high (i.e. high entropy) but stable. As new information enters the system, and exchanges occur, there is a temporary change in the number of options for decision-makers. The system will stabilize again, and depending on the nature of the information and the decisions in process, the level of uncertainty may increase or decrease.

Either way, during the *period of time* when the system absorbs the new information, entropy may increase temporarily if the decision makers must spend time reconsidering their options in light of the new information. This happens when uncertainty arises about how to handle the new information. The length of this unstable time period can vary depending on how much the new information initially increases, but eventually reduces the number of options for the decision maker. Eventually, the number of options decreases and a decision is made from among the fewer options that the new information enabled.

How does a useful system respond to increases and decreases in uncertainty? The process of absorbing information, reconsidering options and the changes in entropy that occur during the decision process is like the annealing of a solid.

Annealing is a process of heating and cooling typically in metals and glass to reduce the number of independent domains and to increase the strength of the material by aligning the molecules into fewer and more coherent domains, thus decreasing the entropy. This heat treatment alters the microstructure of a metal causing changes in properties such as strength and hardness and ductility, whereas in glass, heat is applied to remove stress [14]. Just as metallic annealing is important in the manufacture of useful tools, knives, and swords, information annealing is important for making decisions more reliable and robust with less total uncertainty.

Whereas information annealing or knowledge annealing, has been described as "network-based information system in which all users of the system are permitted to change the system at will," [14], we introduce an alternate type of information annealing called "infodynamic annealing." Unlike annealing in materials, which is characterized by increases and decreases in temperature, infodynamic annealing is characterized by increases and decreases in entropy. These fluctuations in command centers align "particles" of information to increase the usefulness (i.e. strength and flexibility) of the decisions.

Multiple iterations of heating and cooling, proceeding from greater to lesser change with each iteration, enable each particle to find its optimal place in the structure. Thus, the annealing process has been applied algorithmically in information theory to achieve the same effect, i.e. where closed-form solutions are not practical an annealing process is applied to overcome local minima and encourage information particles to settle into their optimal location.

The observation is that organizations appear to be engaged in an ongoing annealing process. Decision-makers gather information and settle into a potential initial decision. As new information is injected into the system, the decision-makers must absorb that information and resettle into a new position with some associated change (even if minor) in confidence. Ideally, the confidence increases but any change is beneficial since the previous level of confidence may have been in some sense a "false" confidence (based on incomplete, incorrect or misleading information). Although not as controlled as physical annealing, infodynamic annealing, i.e. the process of dynamically increasing uncertainty and resettling, appears to be applicable in the decision process and is consistent with the approach to physical models described in this paper.

The infodynamic-annealing efficiency of organizations may vary over time, based on structure or policies that influence empowerment, visibility of information, amount of human-to human communication and the other causal measures that affect information flow. If the force of the information exchanges is weak, the information exchanges may not occur or if they do, the process of absorbing the change through the system will be slow. Consequently, the infodynamic-annealing process may be slow or ineffective or perhaps not occur at all. Organizations that are slow to change and adapt may suffer from and exhibit an ineffective information-annealing capability.

The connection between the physical model and the information decision process has led us to a potential metric for information flow which is simple, understandable, and, according to the model, directly correlated with information flow. The metric is the number of times and speed with which members of the organization exhibits a stage of the annealing process. In other words, how often and how quickly do members of the organization adjust their confidence in their decisions based on new information?

The question to a member of an organization, if we use a survey technique, might be as simple as, "How confident are you in your decisions? (0 = total uncertainty; 1.00 = absolute confidence)." If we could find an efficient, unobtrusive way to collect an answer from each member of the organization on perhaps at least a daily basis, statistical analysis could assess the number and speed of confidence changes, perhaps informed by the rate of information flow expected for that domain (e.g. accounting, engineering, programming, etc.). The challenge is that the metric would need to be collected often enough to keep pace with the expected rate of change representing a stage of the annealing process. This relates back to the intractability of a closed-form analytical solution of information flow.

Consider the relative amount and speed of changes in confidence and what such a metric might imply based on the physical models described here. If a decision maker never exhibits a change in confidence, even temporary, this suggests poor information flow since no annealing process is indicated. Explanations for this condition could include one or more of the following situations:

- The decision maker is surrounded by support personnel who produce information that corresponds only to what the decision maker wants to hear.
- The decision maker is unwilling to accept information contrary to the status quo.
- The decision maker spends too much time in meetings and direct human-to-human communication. In this case, the bandwidth for receiving new information is too constrained.

Any of the causal measures in the physical model may apply. If a decision maker never exhibits stability in confidence, whether low confidence, high confidence or in-between, even temporarily, this also suggests poor information flow since no annealing process is indicated.

The metric may hold some interest in relation to common perception of confidence. Some may think that effective decision makers strive to maintain high confidence in their decisions. The metric suggests that effective decision makers strive to apply stages of annealing as often and as rapidly as possible and necessary. In other words, effective decision makers focus on the process of incorporating and modifying their confidence in their decisions. Through the application of this process, higher and higher confidence is achieved through constant integration of new information in a process that enables and utilizes changes in confidence (entropy) to optimize the quality of the decision.

7. Conclusion

In this paper, the authors build upon previous work to suggest a physical model for information flow. The implied process of annealing may be measurable by the number and speed of changes in confidence. The goal is to develop a generic, simple, tractable, and understandable metric that correlates with information flow. A physical model equates causal impacts on information flow to physical equivalents of mass, acceleration and force. The resulting interactions of particles suggest a process of dynamic change as information is integrated followed by a phase of stability where the information is absorbed into the decision process. This information process is analogous to the physical process of annealing in metals and glass. In infodynamic annealing, the process is a controlled change in confidence (entropy) in the system. This paper suggests that these changes in confidence may be a key to enabling a simple, understandable metric for information flow. Further research will expand the physical model in this direction to explore this capability. Further research will use the model and simulation method described here to understand better how various causal factors affect the information-flow process.

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