Military Information Networks as Complex Adaptive Systems

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Abstract

New information technology now permits a vastly increased degree of connectivity in military communication networks. This more connected architecture should result in faster response times and greater efficiencies in military operations. A potential downside, however, is that highly connected network architectures are more prone to chaotic behaviors. Unfortunately, these behaviors are: nonlinear, frequently counter intuitive, usually manifested only under severe stress, and difficult to discern under the "artificial" conditions of training exercises. This paper introduces a methodology and a set of tools for the simulation of nonlinear network behaviors. The approach taken is to consider military information networks to be complex adaptive systems made up of autonomous decision nodes (of variable capacity and responsiveness) coupled by information flows (of variable urgencies and multiplicities). A coupled-map-lattice approach to the simulation of network dynamic behavior (greatly facilitated via the recursive functions of the *Mathematica*^{tm} software package) is employed. Although simplistic, this approach may possess the appropriate degree of "essential nonlinearity" for use by network designers seeking to hone their nonlinear intuition. If destructive chaotic behaviors can be thereby anticipated and ameliorated prior to their occurrence in military operations, then the promises of information age technology may be fully realized by our nation's military forces.

1. **Introduction**

The science of nonlinear complex adaptive systems (CAS) or Complexity provides a unique perspective for the analysis of the dynamic function of military information networks (MIN). This perspective is of critical importance to the design of network architectures that are robust and stable yet responsive and adaptable under the high stress situations that frequently occur in military command and control operations. This paper introduces a Complexity approach to modeling and simulation of the dynamic behavior of complex MIN and applies this approach to the analysis of some issues that are of importance to the digital battlefield concept. While the specific simulations reported here are extremely simple-minded, they do yield results consistent with the general intuition that led to the digital battlefield mode of thinking. They also yield some counter-intuitive results that suggest the need for further nonlinear analysis of synchronicity issues relating to the digital battlefield.

The concept of an MIN employed here is that of a CAS of multiple decision nodes each of which is itself a CAS (also capable of nonlinear behavior). The CAS at the individual node level is the brain of the human empowered to make decisions relevant to that node together with any advisory staff assigned to that node. A "meta-model" of the human decision process (derived from a branch of cognitive psychology called reflexive modeling) is used to understand the potential chaotic[i] behavior of a single node. In general CAS are products of evolution (this is certainly the case for the human brain) and the CAS concept of an entire MIN implies the need of a certain "Military Darwinism" in the approach to the design of these networks. The inputs to this reflexive decision model are divided into two categories: 1) emotional responses to the situation (feelings), and 2) logical responses to the situation (analysis, thinking). While the reflexive meta-model is not dynamic, some simple and straightforward assumptions regarding the temporal development of its inputs show that a dynamic reflexive decision function should obey the logistic differential equation (in certain well defined circumstances). The logistic differential equation is the continuum form of the discrete logistic map (a favorite toy model of Chaos Theory). A finite neuro-dynamic interpretation of this result suggests that the discrete mapping may be a more faithful representation of real dynamic decision behavior than the continuum differential equation.

These circumstances are used to motivate a dynamic Complexity model of an MIN that is a coupled-map-lattice (CML) in discrete time of information nodes coupled by communications links (of variable architecture and complexity) with the temporal behavior of a single node modeled by the logistic map. The mapping variables are interpreted as information activities (not just communication activities) and the meaning of the various parameters of the CML are discussed within this context. Such a CML will certainly be vulnerable to chaotic behavior under certain circumstances and communications link architectures. This is precisely the behavior that one seeks to investigate in the CML and should seek to avoid in real military command and control networks. This CML approach, together with the recursive mathematical functions of the *Mathematica*[tm] software (NestList, etc.), are offered as a powerful prescription for carrying out the program of Military Darwinism required for the intelligent design of the communications link architectures of MIN in the Information Age.

2. **Chaos and the Human Decision Process**

No one doubts that the human decision process is sometimes chaotic; however, a mathematical model of the process that reflects this property was lacking until recently. The publication of the reflexive decision model of V. Lefebvre[1], based on sound principles of mathematical psychology and nonlinear science, now permits the first real strides in understanding this all too human condition. The model is of a binary choice and is based on the assumption that human decisions are influenced not only by utility considerations (world pressures) but also by value considerations (ethics, morals, prejudice, bias, etc) that are innate to the individual. The model is probabilistic (free will forever denies the possibility of "point prediction" of human decision

[i] Here and throughout this paper the word "chaos" will be used not in the strict mathematical sense of deterministic chaos, but instead as a catchword representing any nonlinear behavior that promotes inefficient operation (or dissipation of effort) of the component under consideration.

behavior) and is based upon three variables that are also given a probabilistic interpretation. Two of these variables (denoted x_1 and x_2) capture the pressures brought to bear on the decision agent by the external world at the subconscious (feeling) and conscious (thinking) levels respectively. A third variable (denoted x_3) captures the input of selfish motive (personal preference, wishes) of the decision agent. The model is represented by a tri-linear polynomial:

$$f(x_1, x_2, x_3) = x_1 + (1 - x_1)(1 - x_2)x_3\,, \qquad (1)$$

which may be interpreted as the probability that the agent will choose the "positive pole" (assigned either consciously or subconsciously according to the agent's values) of the binary choice. This interpretation rests on the convention that the integer 0 represents the negative pole and the integer 1 the positive pole of the binary choice. This function is based upon a further assumption that all human decisions are self-referential and can be represented in terms of an image-of-self function (a correct one) that depends on only two independent variables:

$$f_s(x, y) = 1 - y + xy\,. \qquad (2)$$

Simple substitution shows that the following (recursive) representation is equivalent to Eq. (1):

$$f(x_1, x_2, x_3) = f_s(x_1, f_s(x_2, x_3))\,. \qquad (3)$$

Although a recursive structure suggests the potential for nonlinear behavior, this model does not display chaotic behavior as long as the input of selfish motive (x_3) is given free rein. Frequently, however, decisions are made that should not include selfish motive as an input (at least not explicitly). These decisions are called "realist choice" and are represented by a function that depends only on the world pressure inputs (x_1 and x_2). This function may be found by replacing both the selfish choice function and the x_3 variable of Eq. (1) by the realist choice function:

$$f_r(x_1, x_2) = \frac{x_1}{x_1 + x_2 - x_1 x_2}\,. \qquad (4)$$

Eq. (4) is indeterminate at the point $x_1 = x_2 = 0$ (maximum world pressures to choose the negative pole). Its limit as this point is approached can be any value between 0 and 1. Lefebvre refers to this as a point of chaotic decisions (although something other than dynamic chaos is meant since this is a static model). The realist choice is the closest that a reflexive agent can come to basing a decision entirely upon utility factors. Space does not permit any further justification of these remarkable decision models; however, readers who would like a detailed derivation together with a discussion of some alternative models of decision agents whose self-image functions are less perfect representations of reality may consult the author's presentation[2] at the Workshop on Multi-Reflexive Models of Agent Behavior, Los Alamos, New Mexico, 1998.

Eq. (4) represents the probability of (realist) choice of the positive pole at the "moment of decision," but this static function offers no guidance as to the temporal development of this decision probability (what the decision probability might have been if the agent's moment of decision had been forced at an earlier time). One can, nevertheless, infer something about this temporal development by consideration of the likely temporal behaviors of the variables x_1 and x_2. The variable x_1 is associated with the agent's feelings regarding the situation. Feelings are primarily a function of (subconscious) pattern recognition and are normally thought of as occurring instantaneously. The variable x_2, on the other hand, is associated with the agent's thinking, which implies analysis that requires time for development. There is an aspect of instantaneous pattern recognition associated with x_2 as well; however, this is more a matter of classification than analysis. Hence a temporal model of x_2 might have the form[3]:

$$x_2(t) = x_2(0)e^{-\lambda t} + x_2(\infty)(1 - e^{-\lambda t}) . \qquad (5)$$

The parameter λ is designated the cognitive response parameter and determines the speed with which the instantaneous classification $x_2(0)$ is converted into the final limit $x_2(\infty)$ at the moment of decision via the agent's analysis. The agent effectively chooses this parameter based primarily upon time constraints. Now an expression for the time derivative of the realist choice probability function may be obtained via the chain rule:

$$\frac{df_r}{dt} = \frac{\partial f_r}{\partial x_2}\frac{dx_2}{dt} . \qquad (6)$$

By use of the temporal model of x_2 represented by Eq. (5), Eq. (6) may be shown to be equivalent to the following:

$$\frac{df_r}{dt} = \lambda \;\; f_r(1 - f_r) \qquad (7)$$

should either of the following restrictions apply: x_1=1, or $x_2(\infty)$=0.

Eq. (7) is the logistic differential equation. The simplest discrete finite difference approximation to this equation results in the logistic map of Chaos Theory. The cognitive response parameter becomes the bifurcation parameter in this approximation. There is a sense in which this discrete representation may be a more realistic description of brain function than the continuum form due to the discrete nature of neuronal firing. Suppose the brain is modeled as a collection of neurons that vote democratically for or against the choice of the positive pole by either firing or not firing at a set of discrete time steps during their process of mental analysis and the function f_r represents the fraction voting favorably at any one time. Suppose further that these neurons are coupled in a complex way and that each decides whether or not to fire on the next discrete time step by some logical rule that depends only on the firing behavior at the previous time step of those neurons to which it is coupled. Then for any initial value $f_r(0)$ between 0 and 1, the process of neuronal firing will yield a sequence of values $f_r(i)$ that either: 1) converges to a fixed point, 2) converges to a limit cycle, or 3) wanders chaotically. Either of the latter two situations will prevent the sequence convergence that defines the "moment of decision" in this simplistic model and might be associated with the human phenomenon of "hesitation." These are also the possible behaviors of the discrete logistic map for "allowed" values of the bifurcation parameter.

The conditions under which Eq. (7) applies are interesting in their own right. The condition $x_2(\infty)=0$ is expected since it is consistent with the chaotic decision point of the static model (Eq. (4)). The other condition, $x_1=1$, is somewhat surprising since its interpretation suggests a subconscious world pressure in favor of the choice of the positive pole. It is tempting to speculate that this condition might lead to hesitation associated with the human reaction signified by the words "too good to be true." Perhaps not too much should be read into these special conditions, however, since their absence only results in extra terms in Eq. (7); and what we now know about the Universality[4] of nonlinear mappings suggests that similar nonlinear behavior might be expected of discrete approximations to the more general equation.

3. **CML Representation of MIN**

The logistic map will now be employed to represent not just the mental decision activity of a single individual involved in a binary choice situation, but the aggregate of "information activity" of a single node of an MIN. This aggregate includes activities associated with sending and receiving communications, research, analysis, and formulation/transmission of decisions by a command official and his staff. In keeping with the expanded interpretation of the mapping variable, the notation for the logistic map is also changed:

$$I(n+1) = I(n) + \frac{2k(I^{\max} - I(n))(I^{\min} - I(n))}{I^{\max} - I^{\min}}. \qquad (8)$$

With this notation the mapping variable I is no longer restricted to the range 0 to 1, but can be measured in units of any size. The parameters I^{min} and I^{max} are subject to the same unit assumptions and represent respectively a minimum level of activity (the I'm awake level) and a maximum sustainable level (activity saturation). Figure 1 shows a plot of the limit $I(n\to\infty)$ of this mapping for the specific parameters $I^{min}=20$ and $I^{max}=100$ as a function of the bifurcation parameter k. This notation (Eq.(8)) is chosen such that the first bifurcation occurs at the point k=1 and the entire infinite period doubling cascade, together with the region of deterministic chaos occurs from k=1 to 1.5. This bifurcation structure is universal (independent of the choice of units for I). The parameter I^{min} represents the attracting fixed point below the first bifurcation point (k=1). The rate at which the fixed point is approached in this region varies greatly depending on the value of k. The fixed point is approached very slowly for values of k near zero and is approached most rapidly as $k\to 1$. The parameter k will thus be designated the reactivity parameter (responsiveness to new information) and used to distinguish between: 1) the rapid responses of tactical force nodes (near the "pointy end of the stick"), 2) the more measured responses of operational nodes (where mid-level command authority pertains), and 3) the even more studied responses of strategic nodes (where the highest level of command authority is vested). Values of k above the first bifurcation point are inappropriate for use in this context unless employed to represent a node consisting of untrained personnel who tend to over-react to almost any information operational requirement. The parameter I^{max} is the repeller of the mapping in Eq. (8) for positive values of the parameter k (the only values considered here), hence any initial activity level $I<I^{max}$ will seek the fixed point (I^{min}) upon iteration.

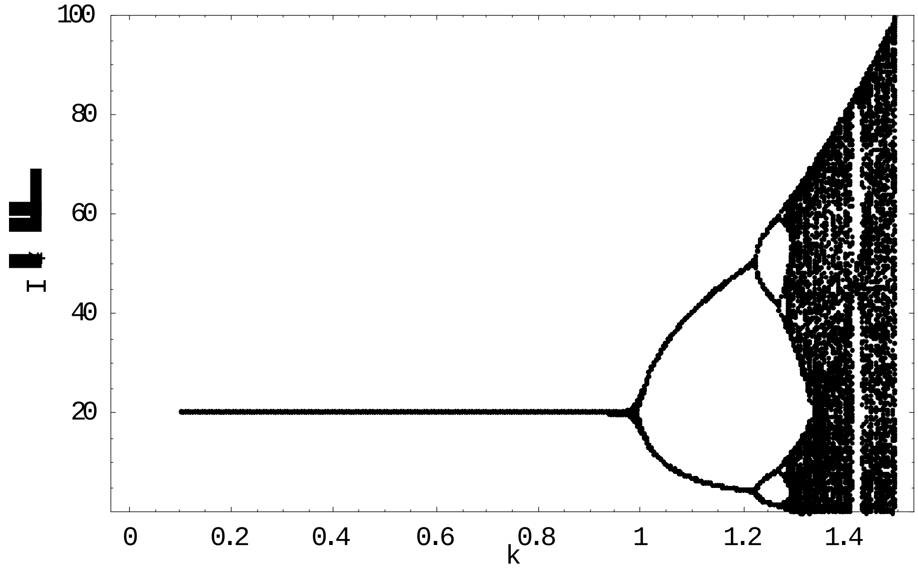

Figure 1. Bifurcation diagram for the Logistic Map (Eq.(8)).

The dynamic behavior of the information activity of an entire MIN will be represented by a CML with multiple nodes linked by communication channels:

$$I_i(n+1) = I_i(n) + 2(I_i^{\max} - I_i(n))k_{ii}\{\frac{I_i^{\min} - I_i(n)}{I_i^{\max} - I_i^{\min}} + \sum_{j \neq i} k_{ij} \frac{I_j(n) - I_j^{\min}}{I_j^{\max} - I_j^{\min}}\} \qquad (9)$$

The parameter k_{ii} in Eq.(9) represents the reactivity parameter of the ith node while the parameter k_{ij} represents the level of urgency of the (binary) communication between nodes i and j. Note that any level of activity of the jth node that is above the minimum (I_j^{min}) will tend to stimulate activity in the ith node, hence this represents a situation where information flows from node j to node i. The interpretation of Eq.(9) as an information activity model will now be given. What this equation says is that at the n+1 time step the level of information activity of the ith node will be equal to the level of information activity at the nth time step plus a term that addresses the information activity imbalance of the situation. This imbalance correction will be proportional to the following: 1) the unused reservoir of information activity (I_i^{max}-I_i(n)) that existed at time step n, 2) the reactivity parameter of the ith node (k_{ii}), and 3) a term that addresses the nature of the information activity imbalance. This last term is the sum of two terms: 1) the internal imbalance (I_i^{min}-I_i(n)) at the nth time step (scaled by the inverse of the difference between the I_i^{max} and I_i^{mix} parameters, and 2) the sum of the amounts by which each jth node exceeded the minimum level of activity at the nth time step (scaled by the urgency of the communication from the jth to the ith node (k_{ij}) divided by the difference between the I_j^{max} and I_j^{mix} parameters). These two terms compete with the former seeking to decrease the ith node activity to its minimum and the latter seeking to increase the ith node level of activity.

To gain some idea of the scaling of the urgency parameter (k_{ij}), some simple simulations of an entirely symmetric information activity exchange between two communicating nodes will be described. These simulations were performed with equal reactivity parameters, with symmetric urgency parameters k_{12}= k_{21}=k, and with symmetric initial activity levels. For values of k<1 the coupled activity levels described by Eq. (9) still decay to their minimum activity levels (also chosen to be equivalent) over time. At k=1 the levels of activity remain fixed at their initial levels (whatever those were chosen to be). For this reason the value k=1 is identified as the "threshold of permanent concern." As k is raised above this threshold, the activity levels approach their maximum (saturation) levels (also chosen to be equivalent) with the speed of approach being determined by the magnitude of the difference (k-1). This approach to the saturation level of activity is monotonic throughout the range k=1 to 2. Above k=2 the saturation level remains the attractor but the approach is non-monotonic with some initial transient overshoot up to k=2.5. This extended range of saturation activity associated with urgency parameters k=1-2.5 reminds one of the old saying that "work expands to fill the time allotted to it." This is the kind of unexpected reflection of human nature that emerges from a Complexity based approach to dynamic MIN simulation. At k=3 the iteration of Eq. (9) no longer converges but, instead, breaks into a two state limit cycle with an activity level that falls above the saturation level at one time step and falls below the saturation level at the next time step. At k=4 the activity levels are more complicated (either chaos or higher order limit cycles with long time transients). These behaviors are not as universal (independent of other system parameters) as the bifurcation behavior of the reactivity parameter, but they do give some important sense of the scaling of the information urgency parameter.

The communications described by Eq. (9) are binary in nature. There is nothing to preclude the addition of triadic forms of communication in this model (or even higher order if necessary):

$$I_i(n+1) = I_i(n) + 2(I_i^{\max} - I_i(n))k_{ii}\{\frac{I_i^{\min} - I_i(n)}{I_i^{\max} - I_i^{\min}} + \sum_{j\neq i} k_{ij}\,\frac{I_j(n) - I_j^{\min}}{I_j^{\max} - I_j^{\min}} + \sum_{k\neq j\neq i} k_{ijk}\,\frac{(I_j(n) - I_j^{\min})(I_k(n) - I_k^{\min})}{(I_j^{\max} - I_j^{\min})(I_k^{\max} - I_k^{\min})}\} \qquad (10)$$

.

The extra term in Eq. (10) represents the kind of communication that a commander might request from two subordinates in a digital battlefield situation where each of the subordinates has information relating to a situation of interest to the commander and the commander orders them to "compare notes" and eliminate duplicate information before delivering a synthesized information packet to him. Binary communication between all three parties would also be necessary to accomplish this. Simulations with Eq. (10) where the reactivity parameter of the command node is less than (5/8th) the reactivity parameters of the tactical nodes and the binary communications necessary to support a triadic communication are all set at the binary threshold of permanent concern show that the threshold of permanent concern in the triadic urgency k_{123} occurs in the range 2.6 to 2.7. As before, an extended range of saturated activity is followed by limit cycles and chaos as the triadic urgency is increased.

4. **Environmental Noise is not Always Bad!**

Situations exist in nature where the performance of a sensing system is actually improved by the presence of environmental noise (Stochastic Resonance). An analogous situation can result from simulations based upon Eq. (10). An anomalous behavior was observed when these equations were applied to the simulation of a realistic scenario (that will be later described in more detail) with high levels of urgency and with an information stimulus that decays with time. For simulations that were virtually identical, a nodal activity history might saturate for a finite time and then decay to the minimum in one simulation, while the same nodal activity history would saturate and remain so forever in another. These qualitatively different forms of behavior did not seem compatible with the trivial differences in successive simulations and there was no obvious predictability to them. Finally, the reason for this anomalous behavior was discovered. As the level of network stress from information of high urgency increases (because of an increasing information stimulus) the saturated activity levels may become attractors rather than repellors. As the level of stress in a situation decreases due to decay of the stimulating information, these saturated attractors revert back to repellors. If the period of saturation persists for a large time, however, the transients of the mapping variables may be eliminated (become too small to be represented in the finite precision of the *Mathematica*[tm] calculations) and the mapping variables become precisely equivalent to the saturation parameters. Lacking these transients, the mapping becomes stuck on the unstable fixed points (repellors). Rather trivial changes in initial simulation parameters can trigger this repellor sticking behavior. Since transient elimination is responsible for this repellor sticking, a low level of random noise can eliminate the anomalous behavior. The MIN simulation equations that are actually used in the results reported here are thus:

$$
\begin{aligned}
I_i(n+1) = I_i(n) + 2(I_i^{\max} - I_i(n))k_{ii}\{&\frac{I_i^{\min} - I_i(n)}{I_i^{\max} - I_i^{\min}} + \sum_{j\neq i} k_{ij}\,\frac{I_j(n) - I_j^{\min}}{I_j^{\max} - I_j^{\min}} \\
&+ \sum_{k\neq j\neq i} k_{ijk}\,\frac{(I_j(n) - I_j^{\min})(I_k(n) - I_k^{\min})}{(I_j^{\max} - I_j^{\min})(I_k^{\max} - I_k^{\min})}\} + Random \quad Noise(0.1\% \quad level).
\end{aligned}
\tag{11}
$$

Whether one views this noise term as a nod toward realism, or as an artifact to prevent an artificial anomalous behavior associated with numerical round off error; its inclusion is necessary in order to achieve reproducible results. This noise term does render the model non-deterministic, however, and some small variations in results of different simulations using exactly the same input parameters are still present. Unlike the situation without the noise terms, these variations do not affect the qualitative features of the solutions.

5. **Intruder Alert: A Realistic Scenario**

Simulations based upon Eq. (11) of a military intruder alert scenario involving seven information nodes will now be discussed. The situation is depicted schematically in Figure 2. The nodes are designated n_1 … n_7 and are connected via a typical ground force command structure. Node n_1 is considered a strategic command node, nodes n_2 and n_3 are considered operational command nodes, and nodes n_4…n_7 are considered tactical nodes. Each node is located at the center of two concentric circles. The radius of the smaller circle is the minimum information activity parameter of that node while the radius of the larger circle is the maximum sustainable information activity parameter. The lines connecting the nodes depict only command authority. Lines of communication are possible between any two (binary communication) or three (triadic communication) nodes and will be shown in bold to distinguish them from the lines of command

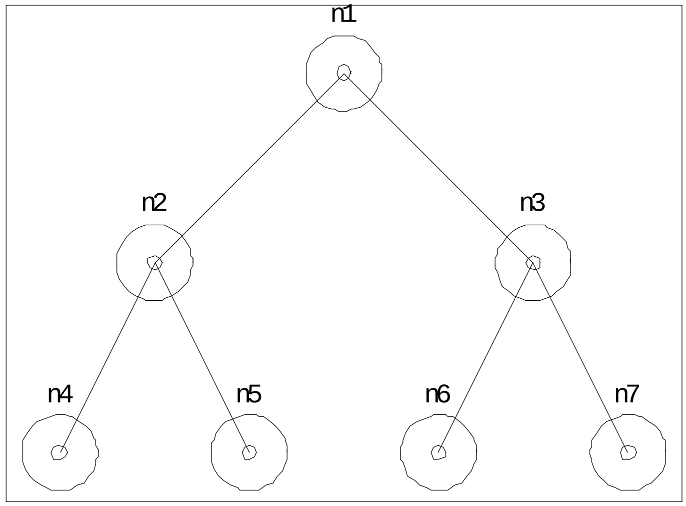

Figure 2. Hierarchical command structure for the intruder alert scenario.

authority. The intruder, which will be depicted by a dark circle, will move from the bottom left of this figure (also thought of as depicting the spatial locations of the nodes) below nodes n_4 and n_5 to the position of node n_6. The simulations will explore the various alternatives by which information about the intruder can be communicated from node n_5 (and sometimes n_4) to the target node n_6. The sensitivity of the various communication architectures to chaotic behavior in response to high levels of urgency (depicted by the radius of the dark intruder circle) of the communicated information will be the primary interest of this study.

The graphic shown in Figure 3 is taken from a *Mathematica*^{tm} notebook that displays an animated sequence (movie) of information activity over time (measured in arbitrary units) that results from the discrete time iterations of Eq (11). This frame (the last of one sequence) shows node n_6 almost covered by the intruder. The communication here flows from nodes n_4 and n_5 (as a triadic communication denoted by the ridge lines of the pyramid) to node n_2 whereupon it flows to node n_1 as a binary communication and finally from n_1 down to node n_6. The necessary supporting binary communications (base of pyramid, urgency specified at the level or permanent concern) are also displayed. The main communication links to node n_6 are given a high level of urgency. The animation sequence shows an instantaneous value for the activity of each node in terms of a dark dot that rotates about the node center (with an angular velocity determined by the nodal reactivity parameter) and with an instantaneous radius determined by the activity value. Watching the movie gives one an impression of how each node is "spun-up" by the intruder alert information. Every node in the figure has a "pen plot" (a small graph showing its prior history of activity). Nodes $n_1 \ldots n_5$ show a saturated activity level throughout most of this sequence while node n_6 shows chaotic nonlinear chatter in response to the high level or urgency. Node n_3 shows

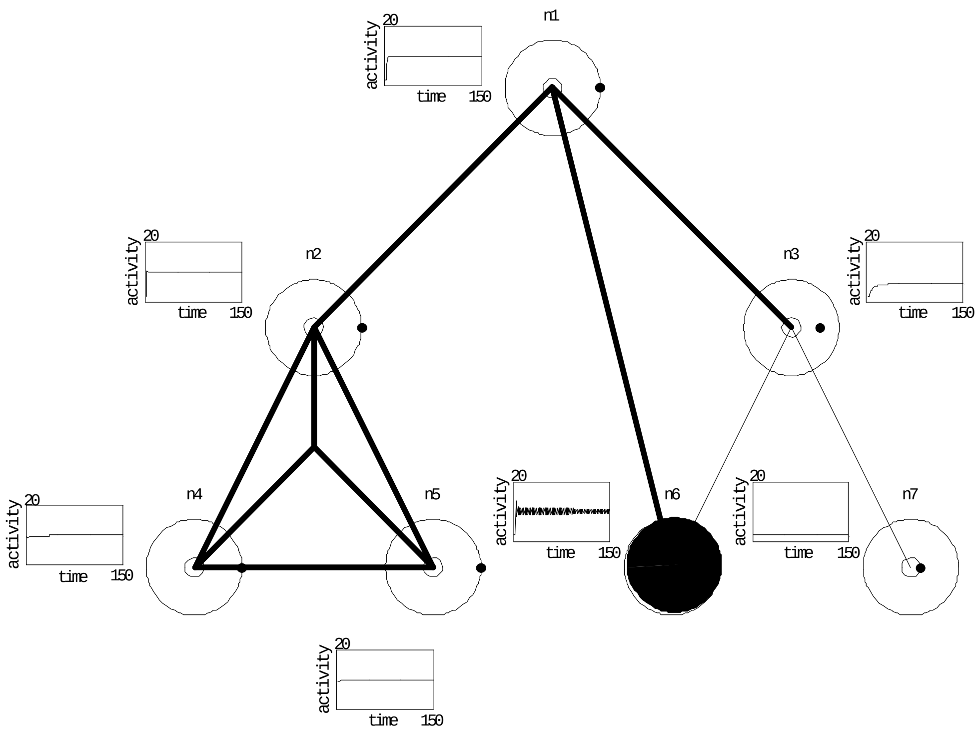

Figure 3. A frame from an animated sequence of information activity history for one communication architecture of the intruder alert scenario.

slightly more than half the saturation level of activity (this node is only being kept informed and not participating directly in advising node n_6). Node n_7 is not participating at all in this simulation and is showing the minimum level of activity. The "pen plots" show the majority of the quantitative information in Fig. (3) and will be viewed exclusively (on a much expanded scale) for the remainder of the discussion. This project was originally initiated in order to develop ways of visualizing the nonlinear behavior of networks (hence the animation).

6. **Intruder Alert: Low Level Urgency**

The first simulation to be described in detail is one in which node n_5 spots the intruder and sends that information to node n_6 via different binary communication architectures. The tactical nodes are all assigned reactivity parameters 0.2 (low enough that most nonlinear behavior results from the coupling urgency, not self excitation), the operational command nodes have reactivity parameters of 0.1 (half that of the tactical nodes), and the strategic command node has reactivity parameter 0.05 (half the operational nodes) for this and all subsequent simulations. All nodes are assigned maximum activity parameters of 10 and minimum activity parameters of 2. The simulation is initiated by setting the n_5 activity level at 9.5 and all others near their minima (2.1). The activity level of n_5 decays naturally to its minimum level in about forty time steps (controlled by the strength of feedback discussed below and the n_5 reactivity). Figure 4 shows the n_6 (target) nodal history curves for four different communication architectures at a low level of urgency (forward communication set at the threshold of permanent concern with a feedback communication at 0.1 times the forward urgency): DC denotes a direct binary communication (between n_5 and n_6), CC denotes a communication that follows the chain of command, ACC (abbreviated chain of command) denotes a communication that uses the chain of command but

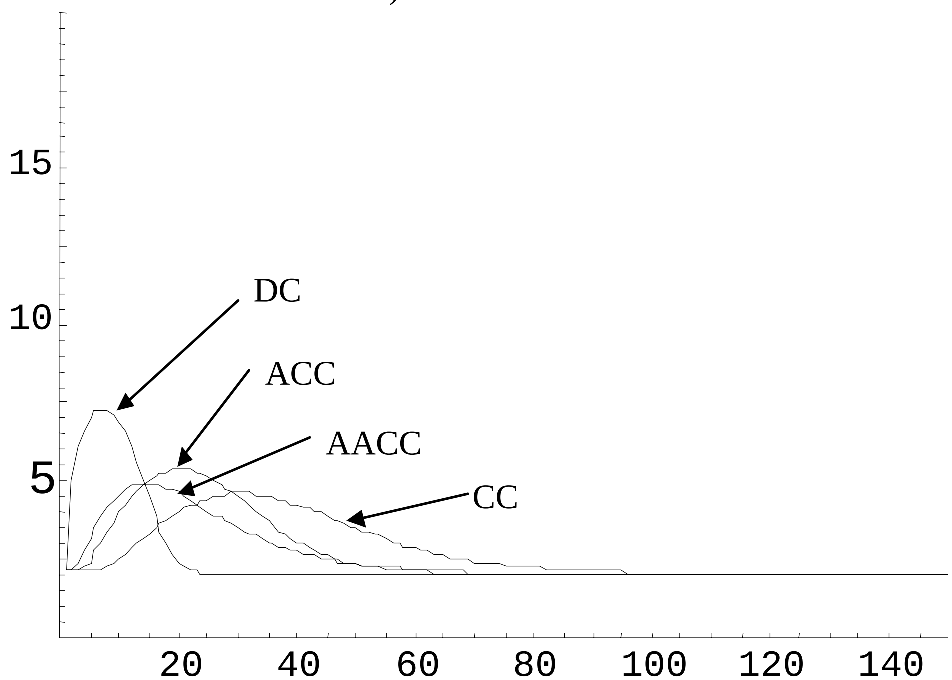

Figure 4. Information activity histories for the target node (n_6) for four different communication architectures (low level of urgency).

by passes the strategic command node by allowing direct communication between nodes n_2 and n_3, AACC (alternate abbreviated chain of command) denotes another abbreviated chain of command architecture whereby direct communications are permitted between the tactical nodes and the strategic command node (by-passing the operational command nodes). These nodal histories display the expected enhanced responsiveness that results from permitting communication channels that are not constrained by the command hierarchy. The DC curve shows the fastest response while the ACC and AACC curves show responses that are intermediate between the DC and CC curves.

7. **Intruder Alert: High Level Urgency**

Figure 5 shows the result of running the same series of simulations with the level of urgency set at six times the “threshold of permanent concern” for the direct communication architecture (DC). Here the n_6 nodal history displays transient chaotic oscillations that decay within twenty time steps; however, the activity remains at the saturation level throughout the simulation. What is somewhat surprising is that the other three communication architectures display somewhat worse nonlinear behavior than that of Fig. (5) (hence they could not be displayed on the same graph) at the same level of urgency. Even the chain of command (Figure 6) architecture (normally considered the most stable and robust) displays initial chaotic oscillations almost as large as those of Fig. (5), and, unlike Fig. (5), this nonlinear chatter persists throughout the entire simulation. The result for the abbreviated chain of command (ACC) is practically indistinguishable from that of the CC. In another surprise, the result for the AACC curve is considerably better than either the CC or ACC and almost as good as the DC curve (see Figure 7). Obviously there are synchronicity issues here that cannot be understood by simple "linear

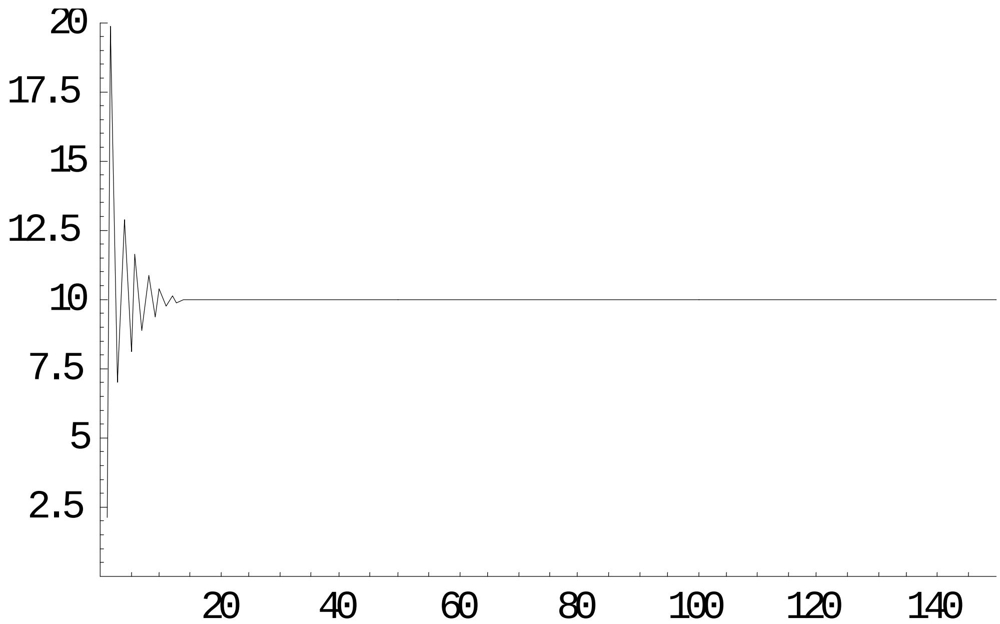

Figure 5. Information activity history (arbitrary time units) for target node (n_6) for direct communication (DC) for a high level of urgency (six times the threshold of permanent concern).

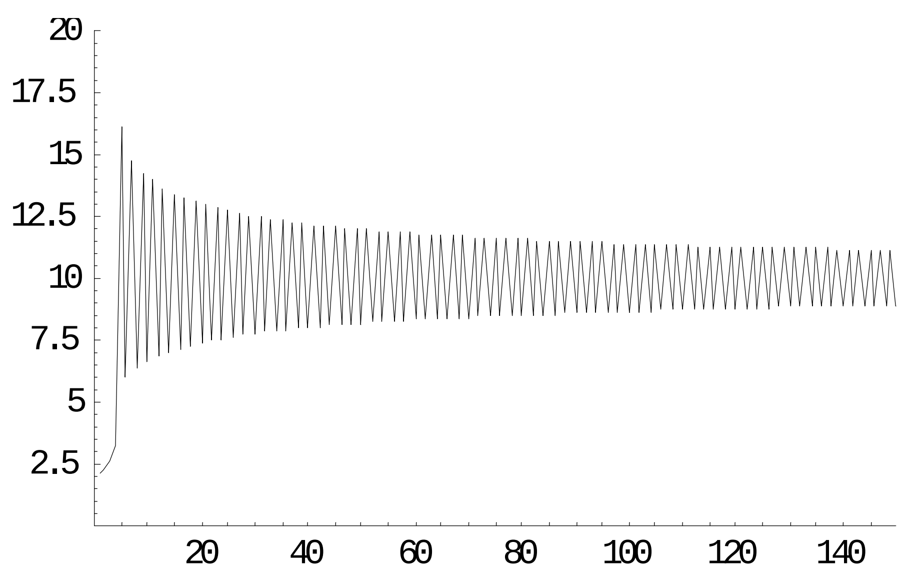

Figure 6. Information activity history (arbitrary time units) for target node (n_6) for chain of command (CC) communication for a high level of urgency (six times the concern threshold).

intuition" that deserve some further study with tools such as these. It is not known whether these issues are sensitive to the exact values of parameters used here (tactical, operational, and strategic reactivity parameters, for example) or are more generic and widely applicable.

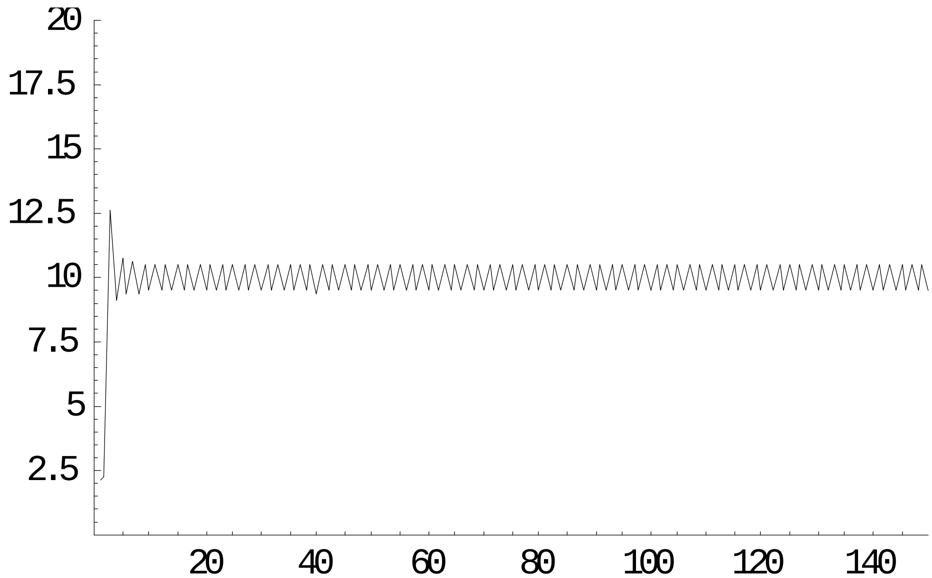

Figure 7. Information activity history (arbitrary time units) for target node (n_6) for the alternate abbreviated chain of command (AACC) communication for a high level of urgency (six times the concern threshold).

8. **Are Fully Connected Architectures Best?**

So far, the more open communication architectures have not proved more prone to chaos in these investigations. Their vulnerability becomes apparent, however, in the simulations that are now addressed. Consider a small variation on the intruder alert scenario such that both nodes n_4 and n_5 spot the intruder and seek to communicate that information through the network. One such situation was depicted in Fig. (3) where nodes n_4 and n_5 form a triadic communication with node n_2. The triadic form of communication works best when the receiving node has command authority over the sending node. For the direct communication variant in this scenario, however, the receiving node (n_6) does not have command authority over the sending nodes and the simulation was performed, instead, with dual binary communications. The network was incapable of supporting the high urgency level in this case (the mapping equations exhibited exponential divergence when the urgency level surpassed four times the threshold of permanent concern). The alternate abbreviated chain of command (AACC) was the least prone to chaos in this scenario (once again performing significantly better than ACC for unknown reasons). Space does not permit the display of these results, but the lesson is that complete freedom to communicate may sometimes be dangerous.

Another phenomenon was investigated with Eq. (11): task sharing. When the urgency parameters of Eq. (11) are positive, activity at the sending node stimulates activity at the receiving node. For negative values the opposite is true. In this case activity at the sending node suppresses receiving node activity. This allows a node that is overwhelmed with work to open a communication with a less busy node and lessen its workload by receiving feedback with a negative urgency parameter. One such simulation was performed to alleviate the high level of chaotic activity of node n_6 through task sharing with node n_7. This simulation was successful at raising the divergence threshold for n_6. Again space does not permit the display of these results.

9. **Is Network Chaos Real?**

A relevant question is whether or not the chaotic behaviors of networks simulated by Eq. (11) have any correspondence with behaviors of real networks. Two examples will be cited that suggest an answer in the affirmative. Both of these examples involve real networks whose chaotic (or nonlinear) behavior is being “calmed” by techniques that have been developed through nonlinear analysis. These and other similar techniques when applied to complex MIN will constitute the first steps in the program of “Military Darwinism” mentioned in the introduction. Real networks become inefficient (dissipative) in the presence of chaotic (nonlinear) behavior; however, the nonlinear chatter of simulations based on Eq. (11) is just a mnemonic for inefficiency (Eq.(11) does not have real dissipative terms). The realism of these simulations is more associated with finding the locations in parameter space where non-linearity is likely to occur, rather than realistic descriptions of nonlinear dissipative behaviors.

The first example concerns chaotic behavior of INTERNET traffic caused by saturation of memory buffers in routers (computers whose function is to receive information packets, determine the most efficient route to their final destination, and send them on their way). A California based company (Network Physics) is developing software solutions for solving the router congestion problem (currently, routers drop packets when their memory buffers become saturated, requiring packets to be retransmitted)[5]. Several commercial INTERNET companies (including Yahoo) are testing the Network Physics methods and reportedly are seeing a decrease in the number of retransmissions. The second example concerns a new treatment for Parkinson’s disease. The tremors of patients suffering from Parkinson’s disease are caused by neurons in the brain that become (too strongly) coupled in an inappropriate synchronous firing pattern because of a lack of the chemical dopamine. This is not chaos, but similar to limit cycle behavior that frequently precedes chaos in networks. These neurons control muscle movement and cause muscle twitching that is responsible for the tremors. There are two treatments for the disorder: drugs, and electrical stimulation of the brain via surgical implantation of a small generator. Currently, this electrical stimulation involves delivering electrical pulses to the patient’s brains at a rate of 120 times a second and effectively breaks the synchrony of neuronal firing. A German medical researcher has predicted on the basis of nonlinear analysis that the synchrony of neuronal firing can be broken by a much less invasive procedure involving only the occasional delivery of pairs of electrical pulses[6]. If proved successful in human trials, this new procedure will benefit patients by significantly reducing the side effects of the current procedure and decreasing the frequency of required surgery to replace spent batteries. A general review of the nonlinear behaviors of complex networks has recently appeared in Nature.[7]

10. **Conclusions**

The simplistic simulations presented show the expected increases in responsiveness permitted by more open communication architectures; but also suggest that something intermediate between the constrained "chain of command" and the fully open (anyone can communicate with anyone else) model is better for suppressing dangerous nonlinear dissipative network behaviors. This method shows promise for addressing synchronicity issues provided that the reactivity parameters of different nodes can be correctly matched with the different reaction rates of real forces. The methodology developed and briefly explored in this paper constitutes a new approach to the study and design of military information network architectures for stability, robustness, and adaptability under high stress. Hopefully these methods are a small step in the direction of preventing costly surprises associated with the unintended consequences of the utilization of new information technology on a future battlefield.

References

[1] Lefebvre, V., **The Cosmic Subject,** Russian Academy of Sciences Institute of Psychology Press, Moscow, 1997.
[2] Miller, L. D., and M. F. Sulcoski, "Reflexive Models of Human Behavior: Variations on a Lefebvre Theme," Proceedings of the Workshop on Multi-Reflexive Models of Agent Behavior," ARL-SR-64, May 1999.
[3] Lefebvre, V., "Sketch of Reflexive Game Theory," Proceedings of the Workshop on Multi-Reflexive Models of Agent Behavior," ARL-SR-64, May 1999.
[4] Feigenbaum, M. J., "Quantitative Universality for a Class of Nonlinear Transformations," J. Statistical Phys. **19**, 25(1978).
[5] Sincell, M., "Physicist use Chaos to Calm the Web," Physics World, News and Analysis, March 2001, p. 7.
[6] Cartlidge, E., "New Treatment for Parkinson's Disease," Physics World, News and Analysis, March 2001, p. 6.
[7] Strogatz, S. H., "Exploring Complex Networks," Nature **410**, 268(2001).