Network Topology and Military Performance

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EXTENDED ABSTRACT

In this paper, we describe a new agent-based simulation system for studying the impact of network topology on military combat performance. Since the timescales of message transfer and agent movement can differ significantly, the simulation is **event-based** rather than time-step. Figure (i) shows a snapshot of the simulation in operation.

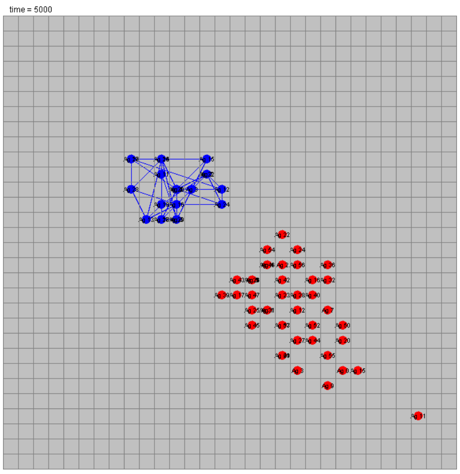

Figure (i). Snapshot of Combat Simulation

The networks we explore in this paper are generated using the process introduced by Kawachi *et al* (2004), which alters the topology of a network without altering the number of links. By varying the parameter p, the Kawachi process can generate regular ($p = 0$), "Small-World" ($0.02 \le p \le 0.1$), random ($0.5 \le p \le 1$), and "Scale-Free" ($p \ge 2$) networks. Figure (ii) shows the values of four network metrics as p is varied: the average distance D between nodes, the clustering coefficient C, the node connectivity K (a measure of robustness), and the symmetry ratio r.

The "Small-World" and random networks correspond to **phase transitions** where network metrics change slowly with respect to p. In particular, random networks are characterised by the clustering coefficient C reaching a minimum and the symmetry ratio r reaching a maximum, with the average distance D between nodes low, and the node connectivity K close to the minimum value of one.

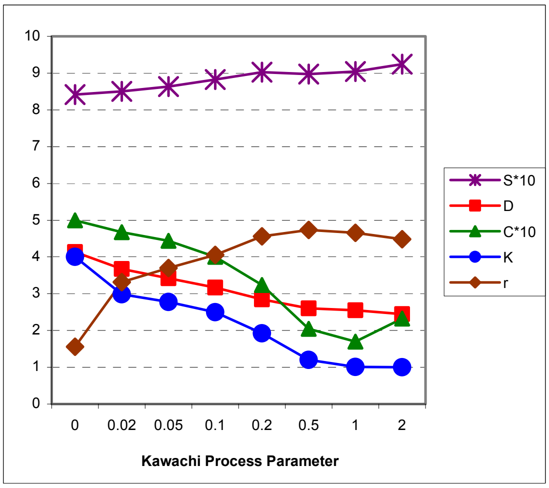

Figure (ii). Values of Average Distance (D), Clustering Coefficient (C), Node Connectivity (K), Symmetry Ratio (r), and Performance Score (S) for different values of the Kawachi Process parameter

In the experiment reported here, and shown in Figure (i), a simulated networked friendly force of 30 agents was engaged in combat with a hostile force of 60 non-networked (but otherwise identical) agents. Figure (ii) shows the combat performance scores S, defined to be the logarithm of the Adjusted Loss Exchange Ratio (averaged over 2000 combats for each network). Performance was best for the "Scale-Free" ($p = 2$) case.

Network performance was best explained as a function of $1/D$. This is consistent with past work (Dekker 2002a, 2002b, 2003, 2004) in which the intelligence coefficient was the best predictor, since the intelligence coefficient is proportional to $1/D$ in this case. The dependence on D was confirmed by using a simple star network, with 29 nodes connected to one central hub ($D = 1.93$). The star network had an average score of 1.002 over 2000 runs, an improvement of 8% on the $p = 2$ case.

Unlike past studies (Dekker 2004), the node connectivity K had no effect on performance. This is because the networked force in the present experiment possessed **tactical agility**: the combination of near-perfect sensor information, rapid reliable communications, and the ability to evade and retaliate against threats.

1. INTRODUCTION

In previous work (Dekker 2003, 2004) we have used modelling and simulation to explore the impact of communications network topology on the performance of a military force. In doing so, we extended the data farming (Horne 1997) approach of Project Albert (Horne *et al* 2000), which uses simple agent-based combat simulations operating with discrete time-steps in a grid-based world. In our extension, which we call network farming (Dekker 2005), we add networking between agents, and study the relationship between network characteristics and combat performance.

Since combat performance is easily quantified, and dependent on information transmitted across the network, such studies are a useful way of studying network effectiveness.

However, message-passing across a network potentially operates on very different timescales from agent movement, and in this paper, we present an improved **event-based** simulation which allows such a range of different timescales.

We use the simulation to study the effect of different network topologies generated by the process of Kawachi *et al* (2004). This process can, by varying one parameter, generate regular, "Small-World," random, and "Scale-Free" networks.

2. THE KAWACHI PROCESS

In the 1990s, Duncan Watts introduced the concept of "Small-World" networks, which have small average distance between nodes (Watts 2003). He also described a generation process which begins with a regular network of large diameter, and "rewires" links (to a random pair of nodes) with probability p. For small values of p, this produces a "Small-World" network, while with $p = 1$ it produces an Erdős-Rényi random network (Bollobás 2001).

Kawachi *et al* (2004) introduced an extension to this process, where the rewiring is biased so as to preferentially move links to be adjacent to highly linked nodes (nodes of high degree). In particular, the link a—b (where a has higher degree) is replaced by a—c, where c is chosen with probability proportional to its degree plus one.

The rewiring is done with probability $p/3$, and the rewiring is repeated three times, so that the probability of an edge being rewired is $1-(1-p/3)^3$. If the resulting network is disconnected, the entire process is repeated from the beginning.

For low values of p, the Kawachi process has almost exactly the same behaviour as the Watts process, and produces "Small-World" networks, but for higher values of p ($p \geq 2$), a "Scale-Free" network (Barabási and Albert 1999, Barabási 2002, Albert and Barabási 2002) is produced.

The Kawachi process is thus an important breakthrough in network theory: it provides a uniform way of generating four important families of network: Regular, "Small-World," Random, and "Scale-Free." This is the process which we use to generate networks for our simulations.

Table 1 and Figure 1 show our experimental results for the Kawachi process with a 30-node antiprism (a double ring of degree 4) as an initial network (30 was the largest network size our simulator could handle efficiently). Results are averaged over 200 repeats of the process. Figure 4 illustrates an example rewired network, and Table 1 provides values for four network metrics:

- The average distance D between nodes.
- The clustering coefficient C (Watts 2003). Changes in C with the Kawachi process are discussed in Kawachi *et al* (2004).

Table 1. Average Values (over 200 runs) of Network Metrics and Performance Scores for varying p

	Value of Kawachi Process Parameter p							
	0	**0.02**	**0.05**	**0.1**	**0.2**	**0.5**	**1**	**2**
Average Distance (D)	4.14	3.67	3.42	3.17	2.84	2.61	2.55	2.44
Clustering Coefficient (C)	0.50	0.47	0.44	0.40	0.32	0.20	0.17	0.23
Node Connectivity (K)	4.00	2.99	2.78	2.50	1.93	1.20	1.01	1.00
Symmetry Ratio (r)	1.56	3.32	3.70	4.06	4.56	4.74	4.65	4.48
Performance Score (S)	0.842	0.850	0.863	0.882	0.903	0.897	0.904	0.924
Number of Hubs	0	0	0	0	0.01	0.14	1.33	3.39

- The node connectivity K, which is a measure of network robustness (Gibbons 1985, Dekker and Colbert 2004).
- The symmetry ratio r (Dekker and Colbert 2005), which is the number of eigenvalues of a network divided by its diameter plus one. This provides a better measure of network symmetry than other alternatives. Low values of r indicate symmetrical networks.

Figure 2 and Figure 3 show X-Y plots for these four metrics (for comparison, values for Erdős-Rényi random networks are also shown). Table 1 and Figure 1 also show performance scores (as discussed in Section 5). Table 1 also shows the number of "hubs," as discussed below.

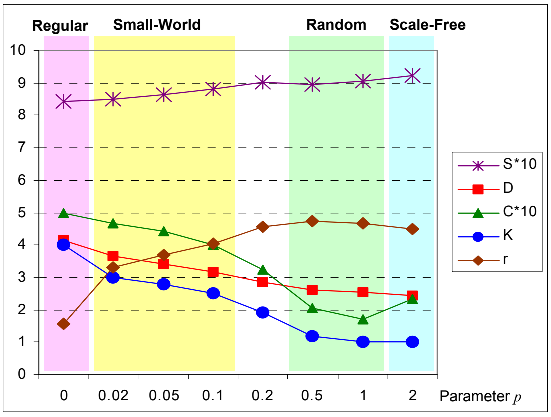

Figure 1. Values of D, C, K, r, and S for varying p

Initially, the average distance D drops sharply as rewired edges are added, and the node connectivity K drops from 4 to an average of about 3. The symmetry ratio r rises sharply as much of the initial symmetry is lost, but the clustering coefficient C changes very little. At $0.02 \leq p \leq 0.1$ there is a **phase transition**, where all four metrics change slowly. The networks in this transitional region are "Small-World" networks.

Figure 4 shows an example (with $p = 0.05$), where the original antiprism links are coloured red, and the new rewired links are coloured blue. This example has average distance $D = 3.10$, clustering coefficient $C = 0.43$, node connectivity $K = 3$, and symmetry ratio $r = 4.29$.

At $0.5 \leq p \leq 1$ there is another phase transition, corresponding approximately to Erdős-Rényi random networks (Kawachi *et al* 2004). Here average distance D and node connectivity K are low, the clustering coefficient C reaches a minimum, and the symmetry ratio r reaches a maximum.

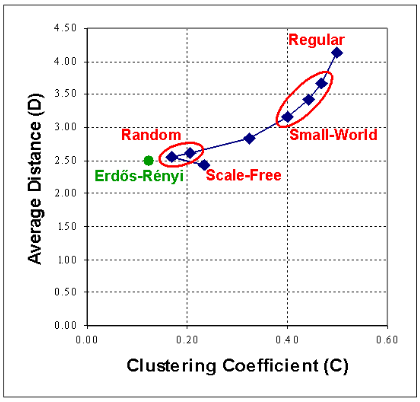

Figure 2. X-Y plot for D and C, for varying p

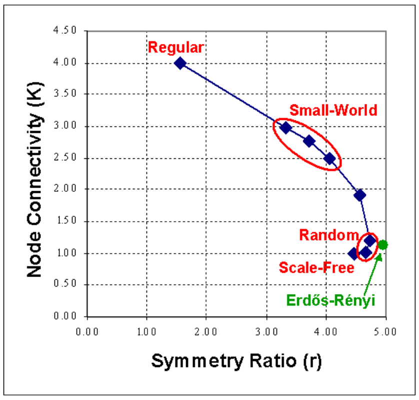

Figure 3. X-Y plot for K and r, for varying p

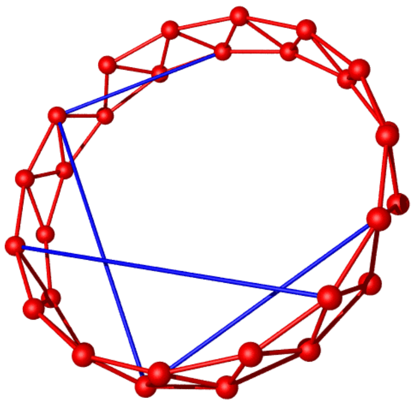

Figure 4. Example "Small-World" rewired network with $p = 0.05$

Finally, at $p = 2$, the networks produced are "Scale-Free" (Kawachi *et al* 2004). Figure 5 shows an example, and Figure 6 shows the log-log plot of degree against rank, which confirms the "Scale-Free" property. For "Scale-Free" networks, the clustering coefficient C actually rises slightly on average (statistically extremely significant at the 10^{-29} level), as observed by Kawachi *et al* (2004).

The symmetry ratio *r* drops slightly on average (statistically very significant at the 10^{-4} level), due to the presence of local "tree-like" symmetry in parts of the network.

Nodes with degree more than twice the average (i.e. more than 8) were called "hubs." Table 1 shows the average number of "hubs," which is initially 0, begins to increase at p = 0.2, and reaches 3.39 for "Scale-Free" networks (p = 2).

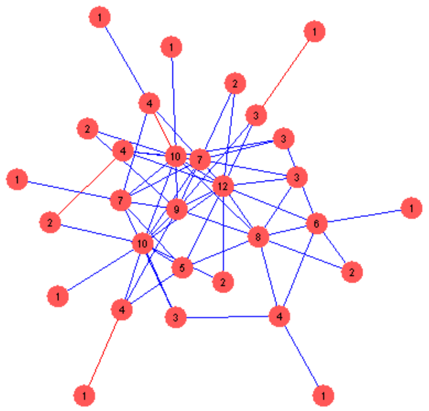

Figure 5. Example "Scale-Free" rewired network with p = 2, showing node degrees

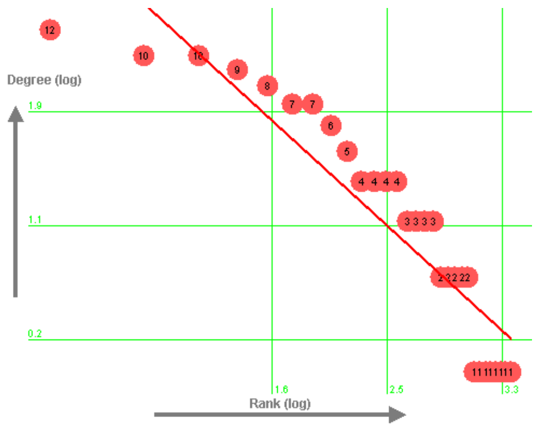

Figure 6. Log-Log plot of degree against rank for "Scale-Free" rewired network with p = 2

3. THE SIMULATION SYSTEM

The agent-based simulation which we have developed involves combat between agents in a grid-based world, such as that shown in Figure 7. Each agent is equipped with a sensor and a weapon. When agents are networked, they broadcast their sensor information across network links to every reachable agent.

The simulation is written in Java, and integrated within the CAVALIER tool for analysing networks (Dekker 2002a, 2002b, 2003, 2004, 2005). Network topologies can be edited using CAVALIER's graphical editing capabilities. The editor can also be used to modify agent properties such as speed or sensor range, and to specify the name of the dynamically loaded Java class which controls the agent's behaviour.

Time within the simulation is (approximately) continuous, and an **event queue** (Graybeal and Pooch 1980) is used to schedule simulation events such as movements or firing.

4. EXPERIMENTAL SETUP

In the experiment reported here, a simulated networked friendly force of 30 agents was engaged in combat with a hostile force of 60 non-networked (but otherwise identical) agents. Having twice as many enemy as friendly agents provided a good test for the benefit of networking. The combat took place on a 30×30 discrete grid, and continued until all the agents on one or the other side were annihilated. Figure 7 shows a snapshot of the simulation in progress, with the networked friendly agents shown in blue, and the hostiles in red. Table 2 describes the values of simulation parameters.

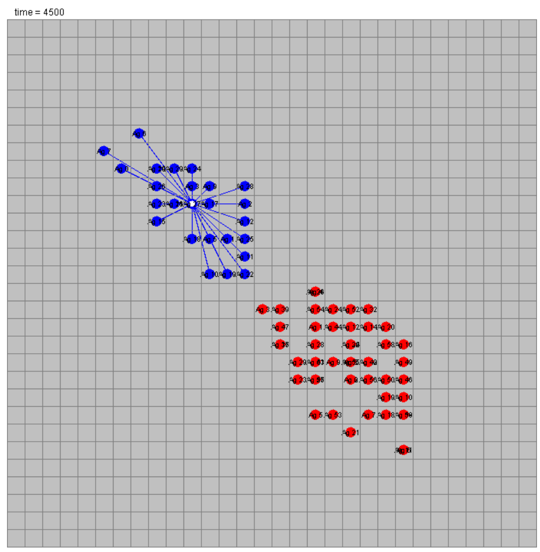

Figure 7. Snapshot of Combat Simulation

Simulations were performed using networks generated by the Kawachi Process, as described in Section 2. Each agent was programmed to move using a combination of attractive and repulsive forces to friendly and enemy agents, as in Reynolds (1987). In the absence of any information about enemies, agents were programmed to move towards the middle of the grid. In the event that "hubs" (agents with more than 8 network links) existed, these were programmed to avoid conflict, while remaining close to the agents they were connected to. The simulation snapshot in Figure 7 includes a "hub."

Table 2. Simulation Parameter Settings

Time to transmit a message across a link:	5 time units
Average time between sensor scans:	80 time units
Average time between shooting:	80 time units
Maximum agent movement speed:	0.005 grid squares per time unit
Sensor range:	4 grid squares
Sensor accuracy:	100%
Weapon range:	8 grid squares
Weapon accuracy:	33%

As a measure of performance for the friendly force, we used the natural logarithm of the Adjusted Loss Exchange Ratio (ALER). To be precise, if C_h are hostile casualties (ranging from 0 to 60), and C_f are friendly casualties (ranging from 0 to 30), our performance score S is given by:

$$S = \ln \text{ALER} = \ln ((1 + C_h) / (1 + C_f)) \qquad (1)$$

This measure of effectiveness has the advantage of being symmetric (inverting the ratio merely changes the sign of the result), and we have used it with success in previous studies (Dekker 2002b, 2003, 2004). It avoids division by zero, and has better statistical properties than the more commonly used loss exchange ratio (C_h / C_f). Specifically, it has the advantage of being almost exactly normally distributed (values of skew and kurtosis are very small: 0.07 and 0.1 respectively). This allows us to use regression analysis to study variation in scores.

To reduce random noise, the score for each randomly generated network was averaged over 10 simulated combat sessions. These averages (for 200 networks for each p value) are shown in Figure 9. The total of 18,000 simulated combats took 27 hours to run on a 2.2 GHz Pentium 4.

5. EXPERIMENTAL RESULTS

For unmodified antiprism networks (p = 0), the average performance score was 0.842, corresponding to an Adjusted Loss-Exchange Ratio of 2.3:1. This is because networking provides sensor information about targets to nodes which are in firing range, but can themselves not see the target.

Figure 8 shows an example, where three networked friendly agents (black dots) can engage the hostile agent (red X), which is in firing range of all three friendly agents (large open circles), even though it is in sensor range (blue circles) for only one agent. The hostile agent, meanwhile, can only retaliate against the one agent it can see.

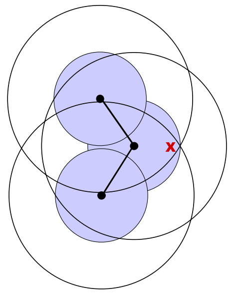

Figure 8. The Network Advantage

The more rapidly this information about targets can be disseminated, the less likely it is that the target will move before it is hit. Performance thus increases with the Kawachi Process parameter p, as shown in Table 1. The average increase in score from 0.842 to 0.924 (corresponding to Adjusted Loss-Exchange Ratios of 2.3:1 to 2.5:1) is modest, since we are merely changing the topology of an already fast network. However, this experiment demonstrates that our simulation software is capable of studying such subtle improvements.

The best predictor of the performance score S was in fact not the Kawachi Process parameter p, but the reciprocal of the average distance D, with the line of best fit being:

$$S \approx 0.73 + 0.47 / D \qquad (2)$$

This equation explains 7% of the variance in performance scores (a correlation 0.26). The correlation is very weak because of the highly random nature of combat outcomes in the simulation. However, the correlation is statistically extremely significant (at the 10^{-25} level). A network with low average distance does not **guarantee** success, but it does improve the odds.

For comparison, we also tried a simple star network, with 29 nodes connected to one central hub, so that average distance was D = 1.93 (even smaller than the 2.44 for p = 2). The star network had an average performance score of 1.002 over 2000 runs. The improvement of 0.078 over the "Scale-Free" network (p = 2) is statistically extremely significant (at the 10^{-12} level). Including this data gave a new best-fit line of:

$$S \approx 0.70 + 0.56 / D \qquad (3)$$

This new equation explains 16% of the variance in performance scores (a correlation of 0.40). Figure 9 shows the best-fit line of Equation 3 overlaid on a scatter plot of the 1800 data points.

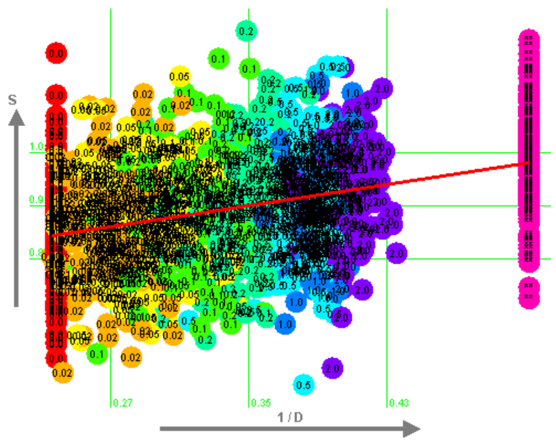

Figure 9. Plot of Performance Score (S) as a Function of $1/D$

In previous work (Dekker 2002a, 2002b, 2003, 2004), we identified a metric which we called the intelligence coefficient as the best predictor of military network performance. For this experimental setup, the intelligence coefficient would be proportional to $1/D$, and so the results presented here are completely consistent with that work.

The other network metrics (C, K, and r) did not explain any more of the variation in performance. In particular, in contrast to a previous combat simulation study (Dekker 2004), the node connectivity K did not have any impact on the results. Indeed, the simple star network (with node connectivity $K = 1$) outperformed all the other networks.

What is the explanation of this apparent conflict? The previous study used a time-step Project-Albert style agent-based simulation with networking added, but where the speed of information transfer was of the same magnitude as the speed of agent movement. Combined with less than 100% accurate sensor information, this made it possible for hostile agents to locate and attack hubs before they were themselves destroyed. In contrast, the present experimental setup has information transfer an order of magnitude faster than agent movement, thus allowing hostile agents to be located and destroyed before getting within sensor range of a hub. The networked force in the present experiment thus possesses **tactical agility**: the combination of near-perfect sensor information, rapid reliable communications, and the ability to evade and retaliate against threats (including threats to the communications network). In such circumstances, node connectivity is not an important contributor to performance.

Tactical agility is best illustrated by the operation of US Air Force fighters controlled by an Airborne Warning and Control System (AWACS) aircraft (Clancy 1995). The AWACS provides near-perfect sensor information, since its radar has line-of-sight over a wide range, and few US opponents possess stealth technology. Communications is rapid, with the AWACS acting as a central hub. There is limited human processing of information, which is conducted efficiently on the AWACS itself, and facilitated by computer equipment. Finally, superior US fighters can (when given superior information) engage most threats, while at the same time protecting the AWACS.

In contrast, the same level of tactical agility is impossible in the land environment, since both the terrain and the civilian population can hide enemies. Large land forces make communications inevitably multi-hop, therefore slower. In addition, threats can appear unexpectedly—for example suicide bombers, or attacks by Special Forces on the communications network.

6. CONCLUSIONS

In this paper, we have described a new agent-based simulation system for studying the impact of network topology on military combat performance. Since the timescales of message transfer and agent movement differ significantly, the simulation is event-based.

The networks we have explored in this paper were generated by the process introduced by Kawachi *et al* (2004), which alters the topology of a network without altering the number of links. By varying the parameter p, the Kawachi process can generate regular, "Small-World," random, and "Scale-Free" networks.

By further investigating the properties of the Kawachi process, we have shown that the "Small-World" and random networks correspond to **phase transitions** where network metrics change slowly with respect to p. In particular, the random networks are characterised by the clustering coefficient C reaching a minimum and the symmetry ratio r reaching a maximum, with the average distance D between nodes low, and node connectivity $K \approx 1$.

Utilising the networks produced by the Kawachi process in our simulation system, our experimental results showed that performance (measured by the logarithm of the Adjusted Loss Exchange Ratio) was best explained by a linear function of $1/D$, where D is the average distance between nodes. This is consistent with past work (Dekker 2002a, 2002b, 2003, 2004) in which the intelligence coefficient was the best predictor, since the intelligence coefficient is proportional to $1/D$ in this case. Our results also emphasise the importance of minimising the average distance D in real-world military networks.

7. ACKNOWLEDGMENTS

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