

Alignment of the Garbage Can and NK Fitness Models: *A Virtual Experiment in the Simulation of Organizations*

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Introduction

Simulation models are finding increasing application and acceptance in the field of organizational theory (Carley and Hill, 2001; Cohen, 1998; Liebrand, 1998). While some work in aligning (or “docking”) different models has been done in recent years (e.g., Axtell, 1996), increased attention to this dimension of model validation stands to increase validity of simulation modeling still further (Burton, 1998). In the virtual experiment summarized in this paper, we demonstrate the technique of docking by developing and comparing results of the canonical Garbage Can model (Cohen, March and Olsen, 1972) with those of the more recent “NK Model” (Kauffman and Levin, 1987; Kauffman et. al, 1988; Kauffman, 1993; Levinthal, 1997). We define a specific domain of comparison of organizational decision-making, formulate propositions with respect to the models’ anticipated results, compare the results empirically, and show that while the models’ behavior is relatively similar their level of mathematical comparability and theoretical integrity is limited.

Objective

Our objective in the virtual experiment described below is to compare the relative performance of the Garbage Can (“GC”) and NK models using a parsimonious set of parameters in each model acting as a proxy for decision making complexity. In their work interpreting initial results of the GC model, Cohen et al. (1972) suggest that the GC decision making process is sensitive to variations in “net energy load”, with increases in such load leading to increased decision difficulty and lower problem resolution. The GC model’s relationship between decisions and load evaluated over a combination of organizational situations is analogous in many respects to the NK model’s intended representation of the relationship between a chromosome’s complexity and its level of epistatic interactions (epistatic interactions are those that occur with other genes in a given gene population and that are local, environmentally induced, and non-additive – that is, non-genetically transferred) over a “fitness landscape.” Although the canonical GC model fixes the number of problems while varying other parameters to assess organizational performance, we vary the number of problems or decisions over a range of complexity levels and then compare results to those from the NK model where the NK model’s number of genes, N , and each gene’s level of interaction, K , represent “number of decisions” and “decision complexity,” respectively.

Approach

Our approach entails development and testing of computer code, canonical model validation, and testing of virtual experiment propositions. For the GC model, we adapted Awk code written by CMU (Lee, 2002) based on an interpretation of the Fortran code originally developed by Cohen et al. (1972). For the NK model, we redeveloped our own version in Awk based on an adaptation by CMU of the C version written by the Sante Fe Institute (Lee, 2002). We selected Awk because of its simplicity and similarity to C and because initial work on much of the code was reusable. In both our adaptation and our custom coding, we focused on just those aspects of each model that we believed represented a reasonable notion of decision making complexity and that would most clearly serve the purpose of illustrating the docking process and testing potential alignment of the models within the scope of the relationship between organizational performance and complexity.

In developing our NK model code, we use Kauffman's basic NK fitness model, where N is defined as the number of gene loci, each with two alleles, 1 and 0, and K is defined as the average number of other loci which epistatically affect the fitness contribution of each locus (Kauffman, 1993). We limit the decision representation to the selection of best local alternatives given information known at the time of the decision, as opposed to randomly selecting from among "better" local alternatives. Since such randomness is already instantiated in the NK paradigm through the assignment and normalization of local fitness values, we believe this reflects organizational theory literature in terms of "satisficing" behavior (Simon, 1976) and represents a rational representation of Kauffman's argument for self-organization in complex adaptive systems (Kauffman, 1993). Kauffman's work also reveals a high degree of correlation in performance (fitness) between landscapes where fitter mutations (or in our case, combinations of decision process and task complexity) are chosen heuristically or randomly from the set of epistatically interacting neighbors, thus making additional modeling (to match those results) redundant.

Following developing and adapting computer code (in Awk), we test each model independently for validity vis-à-vis published results of the canonical versions (Cohen et al., 1972; Kauffman, 1993). Although our experiment itself is limited to a parsimonious interpretation of the respective models and their parameters, we nevertheless show that our reduced versions reflect the same level of veridicality as the original versions of the models with respect to the components we seek to align.

Next, we define how each model simulates the organizational decision task and provides a relative measure of performance. As a self-described "theory of organized anarchy," the GC model by design encompasses only a portion of an organization's activities rather than all of them (Cohen et al., 1972). Likewise, the NK model is necessarily limited in its application to organization theory due to its author's real intention to provide a simplified representation of self-organization in evolutionary biological systems. In addition, neither model addresses aspects of formal organizational or organism structure. Hence, to assess the potential advantages of each model's strengths while minimizing the dilutive effects of dissimilar model variables, we define each model to represent a stylized organization whose purpose is to address a set of decisions or accomplish a set of tasks in an environment of uncertainty. To make this definition concrete and to provide a measure of comparability between the two models, we limit our description of organizational aspects in the GC and NK models as follows:

- Except for relevant parameters defined below, we set all parameters in each model to fixed values. For example in the GC model we set the number of time periods to 20, the number of decision makers to 10, and the solution coefficient to 0.6 for each period. Access structure, distribution of energy and decision structure are varied in the same way as in Cohen et al. (1972). In the NK model, we follow the canonical approach to all aspects of the NK fitness framework and, as dictated in Kauffman (1993), we set the number of alleles, A, to 2, while varying both N and K, where $K \in \{0, 1, \dots, n-1\}$.
- We define remaining independent variables to represent parameters of task/decision complexity faced by an organization, using a combination of the number of decisions with the level of decision interaction as a proxy for decision complexity and uncertainty. The variables used in each model are shown in Table 1.

| Organizational Decision Parameter | Representative Variables | |
|---|--------------------------|----------|
| | Garbage Can Model | NK Model |
| Number of Decisions/Tasks | NPR | N |
| Level of Decision Interaction/Uncertainty | XERP | K |

Table 1. Assignment of Variables.

- We assign the dependent variable of performance to be represented by
 - an adapted output we define as the “percentage of problems resolved” in the GC model, or in terms of GC Fortran variables,

$$1 - \left[\frac{\text{Total number of problems not solved}}{\text{Total number of problems}} \right] \equiv 1 - \left[\frac{KW}{NPR} \right],$$

and by

- the standard output of “NK fitness” from the NK model, represented by a normalized value of weighted “fitness” values resulting from the combined values of N and K. In Kauffman’s paradigm, while the “fitness” value is used primarily in a biochemical context, the author himself mentions that these values can “refer to any well-defined property and its distribution across an ensemble” (Kauffman, 1993, p. 37).

Our reasoning in using these results as a basis for comparison is that we believe a normalized measure of problem resolution is reasonably equivalent to a measure of “fitness” in an organizational performance context.

We then create input data sets to execute each model to simulate organizational performance in the face of small, medium and large numbers of decisions. For each level of decision requirements, we vary decision complexity from low to high over five intervals. Based on this virtual experiment definition, we execute each model 100 times for organizations facing task sizes of 10, 30 and 100. To simulate the range of task complexity faced by these organizations at each task level, we evaluate each task size over the following five levels of decision interaction: at load levels of -44, -33, -22, -11 and 0 in the GC case, and at K levels of approximately 1, N/4, N/2, 3N/4 and N-1 in the NK case (e.g., the K range is 1, 3, 5, 7 and 9 when N=10).

We then formulate two propositions:

Proposition 1: All other modeling elements except load and complexity remaining the same, both the Garbage Can model and Kauffman’s NK model reveal that organizational performance is sensitive to variations in task or decision complexity.

Proposition 2: Both the GC and NK models reflect changes in decision load and complexity in the same direction.

To test these hypotheses, we use the simulation output from each set of 100 runs to develop equations approximating the relationship of performance to changes in decision complexity for each fixed value of number of decisions. Based on those equations, we examine the first derivatives in an attempt to prove the two propositions. We summarize our results in the next section and conclude with a discussion of theoretical implications and additional research opportunities.

Summary of Analysis Results

Step 1: Validation of GC Model Against Canonical Results

In the Garbage Can model, we use the “percentage of problems resolved” as our measure of organizational performance. To validate against the original results by Cohen *et al.*, in Table 2 we compare the proportion of choices that resolve problems under various conditions of load and problem entry times, since this is the closest data the authors present matching our performance measure. Although the results in Cohen *et al.* are not accompanied by standard deviations, thus preventing more rigorous statistical tests of comparison, on face value the results are very close, especially considering the relatively large standard deviations. As summarized in Table 2, results

from the GC model used in this paper are presented at the top in each cell with the standard deviation in parentheses. Results from Cohen et al. are given second in each cell.

| Load | Access Structure | | | |
|--------|---------------------|---------------------|---------------------|---------------------|
| | All | Unsegmented | Hierarchical | Specialized |
| Small | 0.50 (0.31) 0.55 | 0.42 (0.44) 0.38 | 0.47 (0.26) 0.61 | 0.62 (0.07) 0.65 |
| Medium | 0.31 (0.26) 0.30 | 0.07 (0.12) 0.04 | 0.28 (0.24) 0.27 | 0.57 (0.10) 0.60 |
| High | 0.36 (0.34) 0.36 | 0.35 (0.47) 0.35 | 0.26 (0.25) 0.23 | 0.48 (0.21) 0.50 |
| All | 0.39 (0.32) 0.40 | 0.28 (0.40) 0.26 | 0.33 (0.27) 0.37 | 0.56 (0.15) 0.58 |

Table 2. Summary of GC Validation Results (Part 1).

Proportion of choices that resolve problems under four conditions of choice and problem entry times, by load and access structure.

As shown in Table 3, we also compare our results with Cohen et al.'s using several summary statistics calculated by the GC model, providing additional support for our belief that, given the limited detail presented in the authors' original paper, there is a reasonable fit between the canonical version and the re-developed model used in this experiment.

| Load | Summary Statistics | | | |
|--------|--------------------------|------------------------------|--------------------------|--|
| | Mean problem activity | Mean decision maker activity | Mean decision difficulty | Proportion of choices by flight or oversight |
| Small | 112.72 (115.33) 114.9 | 61.20 (36.25) 60.9 | 19.69 (17.46) 19.5 | 0.50 (0.31) 0.45 |
| Medium | 200.79 (103.24 204.3) | 64.16 (39.59) 63.8 | 33.99 (19.13) 32.9 | 0.69 (0.26) 0.70 |
| High | 206.90 (94.34) 211.1 | 75.72 (58.11) 76.6 | 46.61 (28.48) 46.1 | 0.64 (0.34) 0.64 |

Table 3. Summary of GC Validation Results (Part 2).

Proportion of choices that resolve problems under four conditions of choice and problem entry times, by load and access structure.

Step 2: Validation of NK Model Against Canonical Results

Since our version of the NK model assumes the "best local optimum in the adjacent neighborhood" approach, we validate against Kauffman's table of NK results of mean fitness of local optima for nearest neighbor interactions (Kauffman 1993, p. 55). According to Kauffman, the underlying fitness value distribution is approximately normal; furthermore, the central limit theorem provides that means of both Kauffman's and our simulation results are normally distributed. Hence, given the lack of underlying data for Kauffman's results, we use a two-tailed t-test to determine whether our reproduction of NK results is significantly different from the canonical results.

Table 4 shows that for 24 of the 30 mean fitness results compared the null hypothesis $\mu_t = \mu_k$ is not rejected for the critical t-value of 2.62 at 99 percent confidence (where the sample size of our test is 20, and the sample size of Kauffman's test is 100, yielding n_t+n_k-2 or 118 degrees of freedom). Although the null hypothesis is rejected at 99 percent confidence for the remaining 6 cells, the means are still only variant by 2 to 7 percent, and we believe the results are acceptable

for the purpose of an initial proof of concept in attempting to compare results of the GC and NK models.

| K | N | | | | |
|----|-------------|-------------|-------------|-------------|-------------|
| | 8 | 16 | 24 | 48 | 96 |
| 0 | 0.63 (0.05) | 0.68 (0.03) | 0.67 (0.03) | 0.67 (0.04) | 0.71 (0.05) |
| | 0.65 (0.08) | 0.65 (0.06) | 0.66 (0.04) | 0.66 (0.03) | 0.66 (0.02) |
| | 1.108 | 2.177 | 1.059 | 1.283 | 7.513 |
| 2 | 0.70 (0.01) | 0.70 (0.02) | 0.70 (0.03) | 0.71 (0.02) | 0.69 (0.02) |
| | 0.70 (0.07) | 0.70 (0.04) | 0.70 (0.08) | 0.70 (0.02) | 0.71 (0.02) |
| | 0.000 | 0.000 | 0.000 | 2.041 | 4.082 |
| 4 | 0.74 (0.04) | 0.71 (0.04) | 0.70 (0.04) | 0.71 (0.02) | 0.71 (0.02) |
| | 0.70 (0.06) | 0.71 (0.04) | 0.70 (0.04) | 0.70 (0.03) | 0.70 (0.02) |
| | 2.852 | 0.000 | 0.000 | 1.426 | 2.041 |
| 8 | 0.66 (0.04) | 0.71 (0.03) | 0.68 (0.03) | 0.69 (0.02) | 0.69 (0.02) |
| | 0.66 (0.06) | 0.68 (0.04) | 0.68 (0.03) | 0.69 (0.02) | 0.68 (0.02) |
| | 0.000 | 3.176 | 0.000 | 0.000 | 2.041 |
| 16 | | 0.65 (0.02) | 0.65 (0.03) | 0.66 (0.02) | 0.66 (0.01) |
| | | 0.65 (0.04) | 0.66 (0.03) | 0.66 (0.02) | 0.66 (0.02) |
| | | 0.000 | 1.361 | 0.000 | 0.000 |
| 24 | | | 0.63 (0.02) | 0.65 (0.02) | 0.66 (0.02) |
| | | | 0.63 (0.03) | 0.64 (0.02) | 0.64 (0.01) |
| | | | 0.000 | 2.041 | 6.705 |
| 48 | | | | 0.61 (0.02) | 0.61 (0.01) |
| | | | | 0.60 (0.02) | 0.61 (0.01) |
| | | | | 2.041 | 0.000 |
| 96 | | | | | 0.59 (0.01) |
| | | | | | 0.58 (0.01) |
| | | | | | 4.082 |

Table 4. Summary of NK Model Validation Results.

Top line of each cell shows mean (std. dev.) of Ashworth-Louie NK model results ($n_i=20$); Middle line of each cell shows mean (std. dev.) of Kauffman NK model results ($n_i=100$); Bottom line of each cell shows t-statistic for means in that cell (shaded cells indicate rejection).

Step 3: Testing of Propositions

The results of the virtual experiment are shown in Table 5.

| Relative Complexity | Number of Decisions | | |
|-------------------------------|-----------------------------------|--------------------------------------|--------------------------------------|
| | Low GC: NMP = 10 NK: N = 10 | Medium GC: NMP = 30 NK: N = 30 | High GC: NMP = 100 NK: N = 100 |
| GC: Load=-44 NK: K=1 | 0.20 0.69 (0.08) | 0.10 0.69 (0.06) | 0.08 0.67 (0.05) |
| GC: Load=-33 NK: K= N/4 | 0.15 0.71 (0.02) | 0.09 0.69 (0.03) | 0.08 0.64 (0.02) |
| GC: Load=-22 NK: K = N/2 | 0.13 0.72 (0.05) | 0.09 0.67 (0.02) | 0.08 0.61 (0.01) |
| GC: Load=-11 NK: K = 3N/4 | 0.06 0.67 (0.04) | 0.08 0.64 (0.03) | 0.08 0.59 (0.01) |
| GC: Load = 0 NK: K = N - 1 | 0.05 0.65 (0.03) | 0.08 0.63 (0.02) | 0.08 0.58 (0.01) |

Table 5. Virtual Experiment Results.

Proposition 1: All other modeling elements except load and complexity remaining the same, both the Garbage Can model and Kauffman’s NK model reveal that organizational performance is sensitive to variations in task or decision complexity.

Discussion: For each set of results for the GC model, we obtain the following equations:

$$\left. \begin{array}{l} f(\text{load}) = -0.039(\text{load}) + 0.235 \\ f(\text{load}) = 0.0007(\text{load})^2 - 0.0093(\text{load}) + 0.108 \\ f(\text{load}) = 0.08 \end{array} \right\} \begin{array}{l} \text{for } N = 10 \\ \text{for } N = 30 \\ \text{for } N = 100 \end{array} \quad \forall \text{load} \in \{-44, -33, -22, -11, 0\}$$

Each R^2 coefficient exceeds 0.90 for the respective domains, and partial first derivatives of all functions except the one for $N=100$ are non-trivial and non-zero, indicating that the GC model exhibits some sensitivity to low and medium load variations. In the case of high numbers of decisions ($N=100$), the partial first derivative is zero, suggesting that the GC model is indifferent to the level of load or problem complexity when the number of problems is high relative to the authors' maximum level of 20 in the canonical GC version.

For the NK model, we obtain the following equations, all with R^2 coefficients of 0.95 or greater:

$$\left. \begin{array}{l} f(K) = .0031(K/N)^3 - .0371(K/N)^2 + .1184(K/N) + .6043 \\ f(K) = .0033(K/N)^3 - .0321(K/N)^2 + .0745(K/N) + .6440 \\ f(K) = .0008(K/N)^3 - .0039(K/N)^2 - .0248(K/N) + .6980 \end{array} \right\} \begin{array}{l} \text{for } N = 10 \\ \text{for } N = 30 \\ \text{for } N = 100 \end{array} \quad \forall K \in \{0, N/4, N/2, 3N/4, 1\}$$

Clearly, the partial first derivatives are non-trivial and non-zero (see Proposition 2 below) for all three cases, indicating that the NK model within the limitations of this virtual experiment does exhibit sensitivity in organizational performance as complexity increases.

Although the conditions for induction proof are not rigorous (particularly problematical is the GC model's indifference at $N=NPR>100$), we believe that for a domain of comparison where $N \leq 30$ the models reflect organizational performance that is substantially sensitive to variations in task or decision complexity.

Proposition 2: *Both the GC and NK models reflect changes in decision load and complexity in the same direction.*

Discussion. For each set of results for the GC model, we obtain the following partial first derivatives:

$$\left. \begin{array}{l} \frac{\partial f(\text{load})}{\partial \text{load}} = -0.039 \\ \frac{\partial f(\text{load})}{\partial \text{load}} = 0.0014(\text{load}) - 0.0093 \\ \frac{\partial f(\text{load})}{\partial \text{load}} = 0 \end{array} \right\} \forall \text{load} \in \{-44, -33, -22, -11, 0\}$$

And for the NK model, we obtain the following partial first derivatives:

$$\left. \begin{array}{l} \frac{\partial f(K)}{\partial K} = 0.0093K^2 - 0.0742K + 0.1184 \\ \frac{\partial f(K)}{\partial K} = 0.0099K^2 - 0.0642K + 0.0745 \\ \frac{\partial f(K)}{\partial K} = 0.0024K^2 - 0.0078K + 0.0248 \end{array} \right\} \forall K \in \{1, N/4, N/2, 3N/4, N-1\}$$

While the results are inconclusive from a mathematical certainty perspective, an examination of the partial derivatives is instructive. Except for the GC model case where $N=100$ and the NK model where $N=10 \forall K \in \{1,3\}$, over the remaining domains in the virtual experiment the partial first derivatives are non-trivial and decreasing, indicating that over the greatest part of the simulation sample space, both models appear to result in decreasing organizational performance as decision complexity increases. Even so, the lack of mathematical closure is problematical, since it is behavior at the boundaries and extremes (e.g., fewest/greatest decisions, lowest/highest levels of complexity, etc.) where systems dynamics models must display appropriate robustness (Sterman, 2000).

Discussion of Results

While the Garbage Can model and NK models were originally created with disparate motivations, both of the models have notions of task complexity in addition to organizational performance. In our experiment, we examine whether variation of task complexity and number of tasks leads to systematic changes in organizational performance in each model. Furthermore, we seek to determine the extent to which the two models' measures of organizational performance correspond to one another as these variables change.

Rather than finding a perfect correspondence in organizational performance between the two models, we find that the relationship changed depending on what region of the input space the models were in. For example, when the models have a small number of decisions ($N=10$), they both predict that performance will go down as task complexity increases. However, when an organization has a large number of tasks to complete ($N=100$), the Garbage Can model appears to be insensitive to changes in task complexity, whereas the NK model continues to predict that performance decreases as task complexity increases. Looking across all three conditions of number of tasks, the Garbage Can model becomes less sensitive to changes in task complexity as the number of tasks needed to be completed increases. Simultaneously, the performance of organizations in the GC model decreases as the number of tasks increases, suggesting that the number of tasks is more of a determining factor of how well an organization performs than the complexity of the tasks. The implication of the Garbage Can model seems to be that even relatively simple tasks can cause an organization to perform poorly if there are too many tasks to complete. On the other hand, the NK model probably depicts the so-called "complexity catastrophe" (Kauffman, 1993) concept more clearly, since, regardless of the number of decisions, the model results in a clear drop in performance (toward fitness "mediocrity" of 0.50) as the amount of decision interaction increases.

While our conclusions are necessarily limited by the scope of this virtual experiment, the results suggest that additional insight may be gained by taking the alignment of these models to a more rigorous level. Such future analysis might increase the number of input points to further elaborate trends. Additional coding might also help align the sequential decision-making process in the Garbage Can model with the essentially network-oriented process in the NK model. In addition, this experiment is only an attempt at a proof-of-concept, and future work might include tighter statistical validation with no rejected cells, application over wider ranges of numbers of decisions and complexity, and sensitivity tests of results to changes in other parameters in the GC model. And, while our mathematical analysis examined only similarities in directional changes, future work might also encompass the proposition that the models' reactions to changes are in the same relative magnitude.

Comments

The docking process itself, regardless of equivalence outcome, is perhaps the most fruitful part of any comparison of organizational simulation models. The process exposes similarities and differences between the models, making it easier for others to see how the models relate and providing insight into the effects of various computational features. In addition, by uncovering the operational and representation differences, we can more clearly understand the extent to which

each parameter affects model outcomes. In this sense, the docking process serves as a sensitivity analysis of model features on model outcomes.

Our experience with the docking process has been instructive to understanding how the GC and NK models operate and relate to one another, but the endeavor was not free of complications. Validation of each model was particularly troubling; in the case of the Garbage Can model, for example, validation was complicated by the need to convert original Fortran source code to a more widely used programming language. Also, the authors report numerous results yet fail to explain how those results are calculated; for example, Cohen et al. present results using only one out of four possible combinations of choice and problem entry times but do not mention which of the four they present. Thus, the GC model version used for our experiment fails to exactly reproduce the canonical results for any of the four combinations of entry times and instead presents an average value. Furthermore, without actual data, or at the very least standard deviations, for results from the original paper (Cohen et al., 1972), we cannot provide a rigorous statistical analysis to determine how well our version of the Garbage Can model fits the original model. With respect to the NK model, while descriptions of the model are insightful in the literature, existing computer code does not yield comparable results for small and large values of K and requires substantial experimentation in defining the fitness landscape to achieve results close to Kauffman's. Difficulties of this type in reproducing results may diminish the acceptability of validation and docking attempts such as those presented in this and other virtual simulation experiments.

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