# Adaptive Strategies for Improving C2 Performance

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**Abstract**

As units enter combat it is often necessary to change $C^2$ structure in response to external changes such as changing rules of engagement. We demonstrate, using computational analysis, that in a dynamic environment simply changing is insufficient to improve performance; rather, the unit needs to develop the appropriate change strategies. Two meta-strategies can be used for adaptation - tuning and shaking. These strategies can lead to maladaptation if the timing of the shakeups is out of sync with the timing of environmental stressors.

## 1. Introduction

As units enter combat it is often necessary to change the $C^2$ structure in response to various stressors both external (such as changes in the rules of engagement) and internal (such as when a new commander takes charge). Organizational theorists have often suggested that high performance units are those that learn how to learn. This meta learning is often interpreted as acquiring skills, personnel and technology that increase the likelihood that the unit will be able to take advantage of new opportunities when they arise. In contrast, we argue that meta-learning involves not just acquiring "the right stuff" but also developing the right change strategies. In order to achieve high performance, units need to learn strategies for when and how to change and when to take risks.

$C^3I$ systems are clearly complex systems that change frequently thus creating demands for flexibility on the part of supporting software [Leaonardis and Semprini 1986] and supporting flexibility in the organizational architecture. A variety of factors influence the performance of $C^2$ architectures - technology, environmental stressors, rules of engagement and so on. Our concern is with the architecture itself and we ask how can it be designed so that as they change they maintain high performance. Technology alone is not the answer. Even with modern communication technology (such as radios), communication and interference problems (such as the co-cite problem) can be severe [Bahu, 1994] thus necessitating a reliance on SOPs and norms and rules embedded in the $C^2$ architecture.

Herein we are concerned with the impact on unit performance of structural and cognitive factors and the interaction between them. Structural factors include the size, form of the authority structure, and the distribution of tasks. Cognitive factors include the level and type of training and response to external and internal stressors.

## 2. Adaptive Strategies — Tuning and Shaking

A commander faced with a fixed command in terms of the number of personnel has several choices for altering the $C^2$ structure. For example, the commander could change who reports to whom or who is assigned to do what. By making such changes the commander can tune the $C^2$ structure for the extant environment. This tuning process can be characterized as a process of slowly annealing the unit till it

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reaches the necessary level of performance. As the environment changes the commander might wish to rethink these assignments. However, continuing to tune, to make changes like before might not be appropriate. Rather, it might be necessary to rethink the way in which changes are made; i.e., it might be necessary to "shake" things up. Thus the commander has two meta-strategies — tuning and shaking. The question we address is the relative value of these two meta-strategies in improving overall unit level performance.

## 3. ORGAHEAD Model

In this paper, we examine the dynamic relationship between strategy, structure and performance. Using computational analysis we examine the over time behavior of a set of organizations that have the capability of learning both structurally (by altering the connections among personnel and tasks) and operationally (by personnel gaining experience). We will look for evidence of meta-learning; i.e., evidence that the organizations have learned how to learn and so evolved effective change strategies.

The computational analysis is carried out by running a series of virtual experiments using the ORGAHEAD framework [Carley, 1996a; Carley 1998; Carley and Svoboda, 1998]. ORGAHEAD is a dual-level information processing model of strategic adaptation in which the commander can change the $C^2$ architecture in response to various external and internal triggers. At the operational level, each unit is modeled as a set of intelligent adaptive agents (the decision making units - DMU's) arranged in a command structure. Each DMU-agent may be either a person a subgroup, or a platform. Agents are boundedly rational and so exhibit limited attention, memory, information processing capability, and access to information. Unit level performance is determined by the agent's actions as they process tasks. At the strategic level, the commander can alter the $C^2$ architecture strategically in response to changes in the environment and units actual and expected performance. The types of changes examined herein are retasking and reassignment of personnel. Unit performance is affected by the ability of the commander to anticipate the future and take the appropriate strategic actions to alter the $C^2$ structure in response to actual or anticipated environmental changes. This strategic adaptation is modeled as having two components an annealing process whereby the commander tunes the extant structure but at a decreasing rate over time, and a shake-up process whereby the commander alters the likelihood of making major changes in the structure (this can be thought of as increased risk taking).

ORGAHEAD can be thought of as a grounded theory of organizational performance as the behavior of the agents and the features of the model have been chosen to reflect findings from empirical studies of individual human learning and organizational adaptation. ORGAHEAD has sufficient versatility that the user can specify the initial $C^2$ architecture of one or more units, basic training procedures, constraints on agent abilities, the type and likelihood of allowable strategic changes, the maximum frequency of change, the rate of risk aversion, the organization's goal criteria, the task environment, and several types of change "triggers". For example, the $C^2$ architecture can have from 1 to 4 authority levels with 0 to 15 personnel at each level. All of the agents are boundedly rational but they can vary in their retention level and the number of resources they handle (0 to 7) which includes both those needed for communication and for task analysis.

### 3.1 $C^2$ Architecture and Task Environment

The $C^2$ architecture is characterized as a series of networks connecting personnel and resources; specifically, authority (who reports to/commands whom), communication (who talks to whom), and resource access (who has access to what resources). Each of these networks can be characterized using various social network measures of basic features of command and communication structures such as span of control and decentralization. Change in the $C^2$

architectures can be monitored by examining changes in these measures or the extent to which the overall network differs from the unit's initial $C^2$ architecture. As the $C^2$ architecture changes, who reports to whom, who communicates with whom, and who has access to which resources may change. The agent's skill with the resources can vary.

The task is characterized by a nine-bit binary string such that each bit can be thought of as a different, discrete piece of information. In the context of a radar task, the unit responds to a sequence of events determining for each event whether the observed object is a friendly or hostile aircraft or vessel. From a situation awareness perspective, the unit is evaluating context information to determine the overall nature of the threat. The overall task environment is characterized by the bias and volatility in the sequence of tasks. The degree of bias is the degree to which the set of tasks faced by the unit are of the same type or are generated by a similar situation (e.g., friendly). The volatility of the environment is the rapidity with which the type of task faced by the unit changes.

### 3.2 Simulated Annealing

Simulated annealing is a heuristic based optimization procedure intended as a computational analog of the physical process of annealing a solid [Kirkpatrick, Gelatt and Vecchi, 1983; Rutenbar 1989]. The procedural goal is to find that state which minimizes costs. The process involves heating the system to a state that admits many alterations, then, given a cooling schedule in which temperature decreases by some function, slowly cooling the system until it reaches thermodynamic equilibrium at each temperature in this schedule, and eventually freezing the system in a good configuration. This is done by creating a set of moves for changing the existing state to a new state, choosing a move, evaluating the proposed state that this move would create, and then moving to that new state if it improves things and possibly even if it does not. The frequency of accepting such non-improving or risky moves decreases with time (as the temperature cools). Simulated annealing as a heuristic optimization technique it is not guaranteed to find the optimal solution; nor does it always make the best move. Typically, it moves the system to a state that is better than where it started. Simulated annealing is particularly valuable for combinatorial optimization problems which are NP-complete where it may not be possible to locate the exact solution in a reasonable amount of time.

For organizational units, simulated annealing is a computational analog of the process of strategic organizational adaptation through a satisficing process [Carley, 1996b] and has received empirical support as a model of organizational behavior [Eccles and Crane, 1988]. The design of $C^2$ architectures for optimal performance is at least an NP-complete problem.

ORGAHEAD uses simulated annealing to capture the strategic constraint based adaptation process that the unit goes through. Over time, the commander attempts to optimize the $C^2$ architecture relative to some cost function (such as maximize accuracy or kill ratio). The commander alters the $C^2$ architecture strategically; by making changes if it appears to move the unit closer to the goal regardless of whether or not it actually does so [Simon, 1944; March and Simon, 1958]. The commander is not omniscient. Rather than comparing all options the commander simply evaluates a strategy through a kind of "what if" analysis, trying to forecast or anticipate, albeit imperfectly, the future [Allison 1971; Cohen and March 1974; Axelrod 1976]. Since the forecast is known to be imperfect, the commander may gamble on changes that might possibly "increase costs" if it is felt that there is some long term advantage. Overtime, the number of such risky moves decreases [Stinchcombe, 1965] as the unit locks into certain standard operating procedures and so gets trapped by its competency [Levitt and March, 1988].

In ORGAHEAD the commander can change the unit's $C^2$ architecture in a variety of ways. Herein, we are concerned only with two types of change - altering who reports to whom, and altering change who has which resources. These types of changes are the move set used by the annealer, and represent constraints under which the commander must operate. The commander proposes a new design (old design changed by making one of these moves), and then extrapolates the expected performance. In ORGAHEAD the behavior of the proposed new design is actually simulated for a small number of tasks. The performance of proposed architecture is then compared with unit' current performance. In ORGAHEAD the probability of accepting a new design is set by the Metropolis criteria and the Boltzman probability criteria. Accordingly, the commander will always implement the proposed change if the proposed architecture is expected to be a better performer than the current $C^2$ architecture. Otherwise, the risky change is accepted with a small probability which reduces over time (as the system cools). For the virtual experiments that we ran temperature ($T$) drops each time period (until the next shake-up) as $T(t+1) = a * T(t)$ where $a$ is the rate at which the organization becomes risk averse and $t$ is time.

Engineers have postulated that a cooling schedule in which the system is periodically re-heated (shaken-up) will actually increase the likelihood of finding the optimal solution on very complex surfaces [Medeiro, et al., 1994]. Such a cooling schedule is referred to as a Medeiro cooling schedule. In our analyses the shake-ups returned the unit to the original level of riskiness. A direct analog of increasing the temperature is bringing in a new commander. Numerous accounts of battles demonstrate how shake-ups, often associated with a change in command, result in new ways of doing business, potential increase in risk, and increases re-assignment and re-tasking of personnel [Wetterhahn, 1997].

## 4. Virtual Experiment

We explored the parameter space in order to determine the conditions which facilitate meta-learning. This exploration was achieved by running a set of virtual experiments using ORGAHEAD. The set of experiments was conducted across the parameters which are hypothesized to be the most relevant ones in affecting meta-learning.

Task limit, the first parameter, is the simply the number of tasks to which the organization must respond. Since organizations are known to evolve through time and activity, this parameter can be seen as a proxy for time as well, given a naive correspondence between time and activity. We examined organizations under two task limits, 20,000 and 80,000, to determine the differential effects of a longer-term learning period, if any.

Organizations often face tasks of different complexity; that is, the solution space is simply larger and admits many more possibilities than that of a simple task. ORGAHEAD allows for several variations of "complexity". In the experiments presented herein, we define a simple task as one which is comprised of signals that take on only two values, yes or no: a "binary task". A complex task is comprised of signals that can take on three values, yes, no, or neutral/maybe; we refer to these as "trinary tasks". As correct solutions become harder to attain, it is expected that the higher performing organizations will show more complex structures than those which are faced with more simple tasks. That is, we should expect a higher degree of meta-learning and, consequently, the complexity of organizational elements, be they relations, individual attributes or meta-adaptive strategies, to increase as the difficulty of the task increases.

Another means of varying complexity is by varying the amount of information per task. Hence, we explore a second kind of task complexity by observing unit level response to conditions in which the number of bits of information per task is 7 or 9. A third way of increasing task complexity is by not altering the task, but varying the abilities of the individual agent. We do this by varying the number of incoming signals, or bits of information the agent can consider at one time, as either 5 or 7.

We also examine the effect of different kinds of environmental variation on the learning abilities of the virtual organizations. The organizational literature is replete with studies that show how the changing environment, certainly not under the control of the organization, can easily and quickly determine the fate of the organization. Based on these findings, we allow for two types of stressors. The first is simply no stress; that is, the task environment is stable and does not vary. The tasks to which the unit needs to respond remain unchanged throughout the unit's life-cycle as set by the task limit parameter. The second variation involves an oscillating environment in which solution criterion to the task changes periodically. The default condition, also known as no-bias used for the "no variation" condition, requires the unit to classify an input vector as "friendly" or "enemy"; the elements of the input vector can be considered as features of a yet to be identified target or assessed situation. For the "second variation" condition, the unit is put into a state of alert and the criterion for classifying the target as "friendly" becomes much more stringent. For this situation, we say the environment is in a state of "high bias"; the bias is strongly towards the "enemy" classification. So for the "second variation" condition, the environment oscillates every 5,000 tasks between no-bias and high-bias.

While size (i.e. number of personnel) has always been assumed to impact the unit's behavior and performance, the nature of the effect is disputed. For these experiments, we examine unit's which are constrained to have maximum numbers of people per level of 3, 4, 6, and 12. These limits correspond to unit sizes of 9, 12, 18, and 36 respectively.

Finally, we explore the impact of "shaking" by considering four different "shake-up" strategies. The first consists of a single shake-up at the onset as the risk-taking tendencies of the commander slowly decreases over time such that the commander is completely risk-averse by the time the task limit is reached. The second strategy employees an additional second shake-up, the third strategy has three shake-ups, and the fourth has four. When there are multiple shake-ups there is always a shake-up at time 0, and the remaining shake-ups are evenly spaced across the duration of activity as defined by the task limit. So when a four shake-up strategy is employed the unit responding to tasks for 80,000 periods, faces shake-ups at task 0, 20,000, 40,000, and 60,000.

This virtual experiment is described in Table 1. These variations of parameters yield 512 different experimental conditions. For each condition 40 units were simulated, per the Monte Carlo technique, giving us 20480 data observations.

| Parameter | Categories |
|---|---|
| Task limit | 20,000 and 80,000 |
| Task complexity | binary and trinary |
| Environment | stable (no-bias) and oscillating (alternates between no-bias and high-bias) |
| Size | 9, 12, 18, and 36 |
| Individual resources | 5 and 7 |
| Task length | 7 and 9 |
| Shake-ups | 1, 2, 3 and 4 |

**Table 1: Summary of Parameters**

ORGAHEAD has been parametrically constrained in other ways that deserve mention. The primary constraint is that the only the relational aspect of the $C^2$ architecture is allowed to change; this means agents cannot be added or removed. For these experiments, we ask how meta-learning occurs for organizations whose size is fixed. Within this and the aforementioned parameters, each unit's $C^2$ architecture was randomly generated for each run. Changes are allowed to occur every 500 tasks and performance is measured for the same duration as well. Memory capacities are set to 250 tasks, including that of the commander's look-ahead capability. In assessing whether a given change may benefit the organization, commander can look as far as 250 tasks ahead.

## 5. Results

Results from this virtual experiment were examined from a variety of vantage points. We report here on aspects of the findings. First we explore the impact of the meta-adaptation strategies on influencing performance and sustained performance despite environmental and internal stressors. Second we explore the impact of the meta-adaptation strategies on the ultimate form of the resulting $C^2$ architecture. The findings should be treated as a series of predictions that can be explored in human experiments and with field data. Experiments were also conducted to contrast model results with experimental results obtained from the A2C2 project. We note in passing that in general, predictions from the ORGAHEAD model were upheld in this venue.

### 5.1 Impact of Meta-Adaptation on Performance

Our results indicate that, in order of impact, the four factors which most affect sustained performance are: (1) the number of resources available to each agent, (2) the size of the unit, (3) the length of (amount of information in and resources associated with) the task, and (4) the number of shake-ups (Figure 2). These results are summarized in Table 2. Environmental stress (Figure 1), not surprisingly, tends to reduce unit level performance (significant difference at the $p < 0.01$ level). However, the effect of more shake-ups is not strictly linear. We observe that performance slightly increases when the number of shake-ups increases from 1 to 2. Then, a significant drop occurs between 2 and 3 ($p < 0.05$). This degradation is somewhat restored when the number is once again increased to four. One possible explanation for this is that the effect of the shake-up strategy is sensitive to the particular kind and frequency of environmental variation. That is, we should see different effects if the periodicity with which the environment changed did not co-incide with the periodicity of the shake-ups.

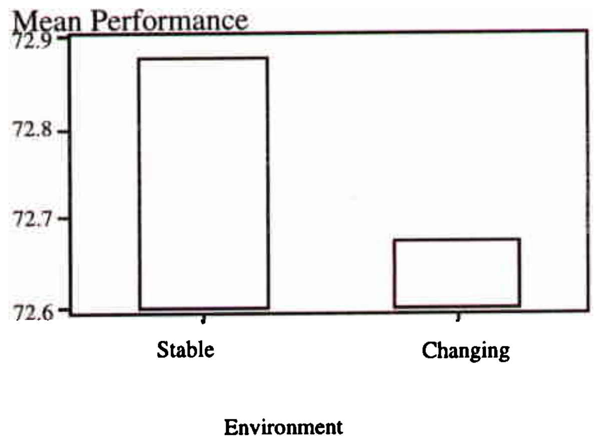


**Figure 1: Task Environment Affects Performance**

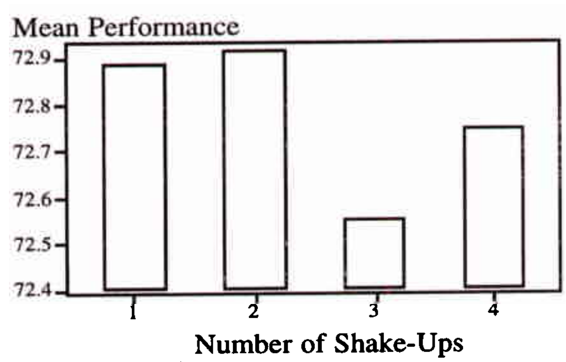


**Figure 2: Interaction Between Shakeups and Performance**

| Predictor | Coefficient | p value |
|---|---|---|
| *intercept* | 0.000000 | 1.000 |
| Task limit | 0.031853 | 0.000 |
| Task complexity | -0.024068 | 0.000 |
| Environment | -0.014568 | 0.027 |
| Size | 0.170226 | 0.000 |
| Individual resources | 0.265205 | 0.000 |
| Task length | 0.091118 | 0.000 |
| Shake-ups | -0.012299 | 0.063 |
| R2 (adj) = 10.9%, df = 7, 20472, p<0.001 | | |

**Table 2: Standardized Regression for Performance.**

Strategies of learning and time to learn are conflated (Figure 3). For lower task duration/experience (i.e. 20000) tasks, annealing strategies have a more varied effect on performance when the environment is unstable. With more history and experience (i.e. 80000 tasks), the reverse is true: application of the consistent strategy yields stable performance levels under the variation.

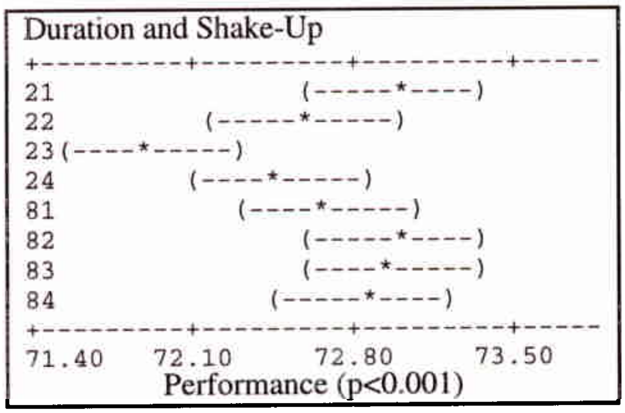


**Figure 3: Duration and Shake-ups affect Performance**

In the changing environment the unit has adapted, or become synchronous, to the variation, while under the stable environmental condition, that goal is more difficult to achieve. Further, the number of personnel per level is a strongly determines he effect of the tuning process; we find that tuning yields more variation in performance for smaller units (Figure 4). Larger units are typically better able to withstand both internal and external stressors. Units that are too large (i.e. size 36) exhibit behavior of smaller organizations; their performance degrades when the environment changes (Figure 5).

## 5.2 Impact of Meta-Adaptation on Architecture

Since there are only a finite number of changes that can be made, the type of change made is indicative of the way in which the unit adapts given a set of constraints. After controlling for task duration (obviously 80,000 tasks will yield far more changes), we look at the difference between the number re-assignments (people-to-people changes) and the number re-taskings (people-to-task changes). Both increasing organizational size and increasing the task complexity from 7 to 9 bits, reduces the number of re-assignments made and increases the number of re-taskings (Table 3).

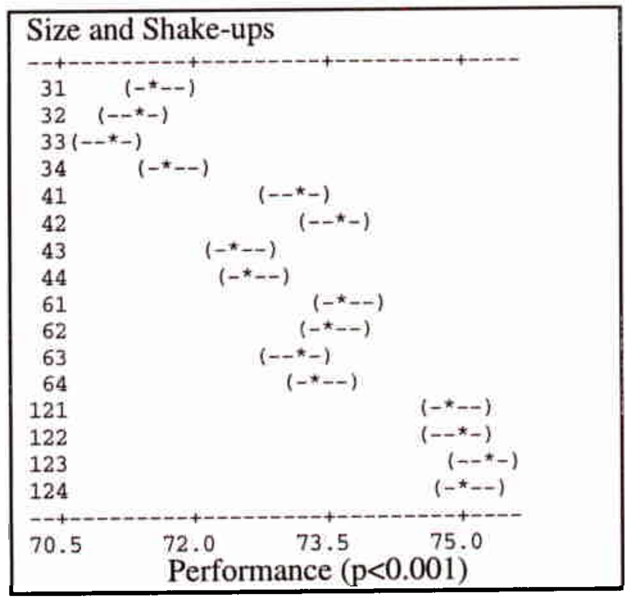


**Figure 4: Size and Shake-ups affect Performance**

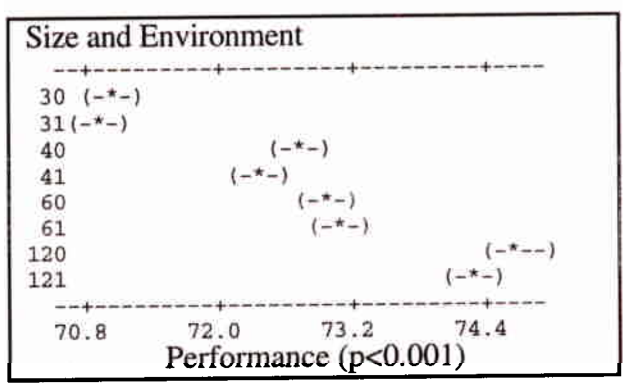


**Figure 5: Size and Environmental Change affect Performance**

This first part of this finding is quite non-intuitive. If there are more people, then the probability of a re-assignment *should* increase. However, we find this number decreases implying that units are adapting by creating more direct linkages to the task and reducing the complexities and noise brought on by inter-organizational communication. The $C^2$ architecture of choice allows for fewer exchanges of information among individuals and increases the among of information and the number of resources available to any one individual. This effect decreases as the task length and difficulty increases. This finding however is more intuitive. The reason here is that as the size of the solution space increases, the direct linkages between the problem-solvers and the task should increase if performance is to be sustained.

| Predictor | Coefficient | p value |
|---|---|---|
| *intercept* | 0.000000 | 1.000 |
| Task limit | -0.005913 | 0.396 |
| Task complexity | 0.009433 | 0.176 |
| Environment | 0.002727 | 0.695 |
| Size | -0.084875 | 0.000 |
| Individual resources | 0.005552 | 0.425 |
| Task length | -0.021738 | 0.002 |
| Shake-ups | -0.004065 | 0.559 |
| R2 (adj) = 0.8%, df = 7, 20472, p<0.001 | | |

**Table 3: Standardized Regression for re-assignment minus re-tasking changes per task cycle.**

The efficiency of the structure is most affected by: 1) the number of resources available to individuals and 2) the length of the task (see Table 4). Units tend to be more efficient in an unstable or changing task environment (Figure 6). The important point here is that efficiency and performance are at odd with each other. Although units in the changing environment have more efficient $C^2$ architectures (this increase in efficiency is significant at the $p < 0.01$ level) they also exhibit lower performance.

What these results suggest is that stress, particularly external stress, can actually improve the efficiency of the $C^2$ architecture. Since unit level performance degrades in a changing environment, this finding suggests that structural efficiency is maladaptive strategy. In other words, redundancy, and not structural efficiency, is needed for the type of flexibility that enables sustained performance in the face of environmental change.

| Predictor | Coefficient | p value |
|---|---|---|
| *intercept* | 0.000000 | 1.000 |
| Task limit | 0.0112216 | 0.001 |
| Task complexity | -0.021989 | 0.004 |
| Environment | -0.019577 | 0.000 |
| Size | 0.041705 | 0.000 |
| Individual resources | -0.224468 | 0.000 |
| Task length | 0.085484 | 0.000 |
| Shake-ups | -0.008307 | 0.220 |
| R2 (adj) = 6.0%, df = 7, 20472, p<0.001 | | |

**Table 4: Standardized Regression for Efficiency.**

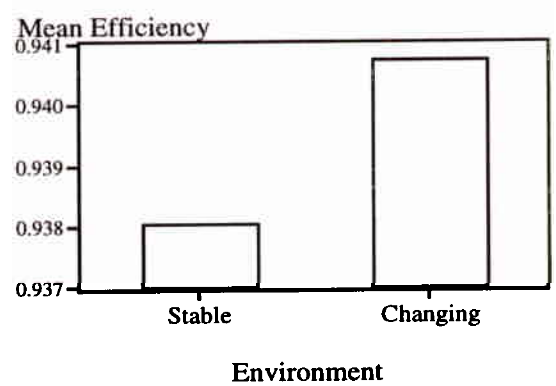


**Figure 6: Environment affects $C^2$ Efficiency**

Certain types of redundancy are more important than others. Although larger units and units with more resources per agent tend to exhibit more sustained performance, other factors also play a role. Connections between personnel or between personnel and resources at different levels have different effects on overall performance and are differentially affected by stressors. In particular, the manager-task, manager-analyst, and commander-task densities are significantly sensitive to whether or not the environment varies. Since we do not observe noticeable differences in performance when the environment varies, it is possible that the unit is sustaining its performance level by adjusting these specific ties in response to environmental stressors. This implies high level connections to lower level personnel and tasks are important when the task environment shifts. Decentralization per se does not sustain performance, rather having a direct line to the commander is of direct benefit.

```
Bias
-------+---------+---------+--------
0                (---------*--------)
1(--------*---------)
-------+---------+---------+--------
     0.840     0.852     0.864
Average Manager-Task Links (p <
0.05)
```

**Figure 7: Bias affects Manager-Task Links**

```
Bias
---+---------+---------+---------+--
0                 (--------*---------)
1(--------*---------)
---+---------+---------+---------+--
  1.065     1.080     1.095     1.110
Average Manager-Analyst Links (p<0.05)
```

**Figure 8: Bias affects Manager-Analyst Links**

```
Bias
+---------+---------+---------+-----
0              (--------*--------)
1(---------*--------)
+---------+---------+---------+-----
0.720     0.732     0.744     0.756
Average Commander-Analyst Links (p<0.10)
```

**Figure 9: Bias affects commander-Analyst Links**

As part of the tuning process the manager-analyst and commander-manager links (Figures 10 and 11) are adjusted. These connections appear to act as some type of homeostatic or mediating mechanisms depending on whether the unit is trying to maintain or improve its performance.

```
Shake-ups
-------+---------+---------+--------
1     (-------*-------)
2              (-------*-------)
3(-------*-------)
4   (-------*-------)
-------+---------+---------+--------
     0.840     0.860     0.880
Average Manager-Analyst Links (p<0.1)
```

**Figure 10: Shake-ups affect Manager-Analyst Links**

```
Shake-ups
---------+---------+---------+------
1                (--------*--------)
2(--------*--------)
3           (--------*--------)
4(--------*--------)
---------+---------+---------+------
       0.615     0.630     0.645
Average Commander-Manager Links
(p<0.05)
```

**Figure 11: Shake-ups affect commander-Manager Links**

## 6. Conclusions

This exploration of adaptation demonstrates that change, in and of itself, is not a viable strategy to sustain high performance in response to changing external and internal operating conditions. Units need to employ meta-strategies for adaptation. One such meta-strategy is to shake things up, for example, by bringing in a new commander. Such shake-ups do not necessarily improve performance. In fact, is the timing of such shake-ups is out of sync with changes in the environment, such a meta-strategy may have very disastrous consequences.

We also found that units respond differentially to external and internal stresses, which are the environmental variation and shake-ups respectively. These effects also vary with the size of the unit and the duration of the task that they face. We find that unit level efficiency and performance can be at odds with each other, particularly in a changing environment. Units with highly efficient $C^2$ architectures are inflexible and tend to be maladaptive in the face of environmental change. The tuning process tends to result in leaner, more efficient, less redundant $C^2$ architectures. In particular, links that skip levels in the organizational hierarchy, that connect the upper levels and lowest levels in the unit tend to emerge. Our analysis suggests that such flattening of the structure, such structural efficiency is potentially maladaptive. The key, to whether or not efficiency improves or sustains performance appears to be in the timing of the shake-ups relative to the timing of the environmental changes. More research is needed on this point.

We observe a decrease in efficiency between managers and analysts; this supports the earlier finding of the negative effects of relational efficiency. Finally, larger more experience units (with more trained personnel) are better capable of withstanding both external and internal stressors. However, there appears to be a point of diminishing return when the unit can become large enough for its size to be detrimental. While, in general, more is better, we see that under certain conditions neither streamlining the organization nor increasing the communication links and raw size necessarily serves to enhance performance. Units ought to be aware of their own risk-taking strategies and the type of environment they are facing before adopting a growth strategy.

Research on $C^3I$ suggests that standard principles such as minimize and prioritize are insufficient in the modern world in which increased complexity and rapid change are requiring greater flexibility. Feedback control and communication control helps to control the adaptivity of the $C^2$ architecture [Clapp and Sworder, 1991]. Additionally, we find that since feedback is often intermittent, incorrect, or based on expectations rather than actualities, meta-adaptive strategies are needed if the unit is to show sustained performance in a changing environment.

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