Laboratory of Economics and Management
Sant'Anna School of Advanced Studies

Piazza Martiri della Libertà, 33 - 56127 PISA (Italy)
Tel. +39-050-883-341 Fax +39-050-883-344
Email: lem@sssup.it Web Page: http://www.sssup.it/~LEM/

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Working Paper Series

The Uneasy Organizational Matching Between Distribution of Knowledge, Divisionof Labor and Incentive Governance

Giovanni Dosi [*]
Daniel Levinthal [°]
Luigi Marengo [ϕ]

[*] *Sant'Anna School of Advanced Studies, Pisa, Italy*
[°] *Wharton School, University of Pennsylvania*
[ϕ] *DSGSS, Università di Teramo*

2002/26 **November 2002**

ISSN (online) 2284-0400

The Uneasy Organizational Matching Between Distribution of Knowledge, Division of Labor and Incentive Governance*

Giovanni DOSI † Daniel LEVINTHAL ‡
Luigi MARENGO §

October 2002

Abstract

In this paper we present a general model of organizational problem-solving in which organizations engage into an activity of cognition (understanding the world in which they operate) and an activity of action (implementing those policies which cognition indicates as targets which better fit the world's characteristics). Both cognition and action are adaptively determined as the organization faces limitations in the cognitive capabilities of its members and in its control functions. Interdependencies among relevant dimensions of the environment and among basic operational tasks are only partly understood. The model allows us to study various combinations of decompositions of cognition and action and various stylized reward systems. In particular, we can address issues of centralization vs. decentralization of cognition, production and rewards schemes and the possible complementarities among these choices.

*Luigi Marengo gratefully acknowledges financial contribution from the European Commission within the project NORMEC (SERD-2000-00316), Research Directorate, 5th framework program. The authors are the only responsible for the opinions expressed in this paper, which are not necessarily those of the European Union or the European Commission.

†Scuola Superiore S. Anna, Pisa, Italy, e-mail: gdosi@sssup.it

‡Wharton School, University of Pennsylvania, Philadelphia, USA, e-mail: levinthal@wharton.upenn.edu

§DSGSS, Università di Teramo, Italy, e-mail: marengo@unite.it

1 Introduction

One of the most fundamental facts about organizations is their hierarchical nature (Michaels (2000), Simon (1981)). Hierarchy is not only an issue for those interested in issues of power and authority structures. Hierarchy is also a central factor if we are to understand organizations as problem-solving entities (Simon 1981) or complex adaptive systems (Lane 1993). As a result, there is an important gap in the evolutionary theory of the firm as originally articulated by Nelson and Winter (1982). While the routine is a powerful unit of analysis with which to explore questions of firm capabilities and differential selection among firms, the puzzle remains as to how organizational routines aggregate and if there is any hierarchical structure to this aggregation. In an important follow-on work, Cohen et al. (1996) pose the idea of a hierarchy of routines.

We suggest that at the apex of this hierarchy of knowledge and capabilities, lie cognitive representations of the environment. What elements in the problem space seem to be interrelated? In what respects is the problem-space decomposable? Given a representation, there is the question of what constitutes a more or less effective strategy. If a firm views the world as being composed of a variety of market positions, as defined by its representation, which of these does it view as being more or less favorable?

Strategy, as an articulation of desired position, is potentially quite distinct from realized behavior. Often, in the business strategy literature, this gap is referred to as the strategy implementation problem (Hrebiniak and Joyce 1984). Within this perspective, such a gap is viewed pejoratively. The organization is viewed as knowing an appropriate course of action but for a variety of incentive and coordination reasons is not realizing that set of policies. Alternatively, the literature on emergent strategy (Mintzberg 1973), (Burgelman 1994) suggests that the divergence between expressed strategy and actual behavior may be a favorable circumstance. The search and discovery that results from such discrepancies may yield the identification of a superior set of actions than that which would be suggested by the conscious choice of strategy.

However, the exploration of the space of possible actions does not, nor should it, be free of constraints or guidance. The space of possible actions is typically vast and large subsets of this space may have disastrous consequences for the firm. Guidance as to what constitutes more or less desired lower-level action may either come from the firm's strategy, based on the conformance between the lower-level action and this strategy, or, alternatively, based on feedback from the environment. The challenge with respect to the latter form of guidance is that the mapping from any given set of lower-level actions to organizational-wide consequences, such as firm's profit or loss or change in market share is quite problematic. Furthermore, such a mapping typically reflects the firm's beliefs about the appropriate decomposition of the problem space in the form of organizational substructures such as product divisions, or profit and cost centers.

We provide an analytical structure that allows us to engage, in at least a stylized manner, this full range of processes. First, we must characterize the problem environment that the firm faces. How binding are the constraints of bounded rationality is a joint consequence of the limits of human cognition (Simon 1955) and the demands of the task environment. In particular, task environments may be more or less complex. A critical facet of complexity is the degree to which a task can be partitioned (Page (1996); Marengo (2000); Marengo et al. (2000)). Tasks that can be partitioned into separable subproblems can be solved via parallel, local problem solving. In contrast, task that cannot be partitioned in this manner, require global, integrated solution efforts, both reducing the speed of solution due to the reduction of parallelism and increasing the span of the required search process.

Given some true task environment, there is the question of how the organization represents this environment. For instance, the true task environment may be nearly decomposable, but the organization may treat it as being relatively non-decomposable. Alternatively, the organization may view the task as being separable into relatively fine-grained chunks, yet the true problem environment is non-decomposable.

The representation structure specifies what elements in the task environment the organization perceives as related or distinct from others. For a given representation, there remains the question of what strategies or policies to specify. This specification of strategy provides a target for lower-level actions. With respect to the organizations internal reward system, though not necessarily the external world, actions that correspond to the espoused strategy should be more highly rewarded than others. Thus, the firm's strategy, and its associated implications for the firm's incentive structure, becomes an artificial, or designed, landscape that actors within the organization climb so as to obtain a higher payoff (Levinthal and Warglien 1999). Actors experiment with alternative behaviors so as to enhance their performance on this artificial landscape. This search itself is constrained by a division of labor within the organization. A subunit can only experiment within the space of behaviors that are controlled by the subunit.

One might naturally assume that the desired division of labor corresponds to the firm's cognitive representation of the task environment. However, such a presumption is not merited. A division of labor that is at odds with the representation may usefully compensate for an incorrect representation. Even if the representation is correct, a finer-grained division of labor may enhance the rate of organizational problem-solving. Indeed, it is to explore the interactions among the cognitive representation, the search for appropriate strategies, and the search for alternative behaviors that prompts our modelling effort.

The following section develops the analytical structure that forms the basis for our modelling. The modelling faces the standard conflicting imperatives of parsimony and completeness. In addition, we wish to provide a structure that is cumulative and connects with prior related efforts. We build on the conceptual foundations of Simon (1981) and subsequent formalization efforts, in particular Page (1996) and Marengo (2000), among others. In the subsequent analysis section, we characterize the basic conceptual insights that are derivable from the model. The effort is not to explore the full combinatoric of parameter settings, but identify the qualitatively distinct behaviors that emerge under distinct and identifiable model conditions. Finally, we conclude with some more general speculations as to the meaning of the current findings and the possible avenues of future research.

2 Model structure

Our model is made up of two elements: the **problem space**, which is exogenously given and characterized by a given degree of difficulty (expressed in terms of sub-problem decomposability) and the **problem solving organization** which searches in the problem space for superior solutions and tries to implement them. We assume that the organization is boundedly rational and therefore carries out its activities through a process of adaptive trial-and-error; at the same time, we also assume that this adaptive search is not purely random but is based on a (albeit possibly wrong) representation of the problem-space.

2.1 Problem Space

The problem-space is an extension and generalization of Kauffman's NK model of fitness landscapes (Kauffman 1993). A fitness landscape is simply a mapping from a vector characterizing an entity's form to a payoff value. The original structure developed by Kauffman postulated a random interaction structure where a given element interacted with K randomly specified other elements. In the spirit of Simon's work on nearly decomposable systems and building on the modelling approaches of Marengo (2000), Marengo et al. (2000) and Ethiraj and Levinthal (2002), we characterize problem environments as potentially consisting of more structured patterns of interaction.

More formally, the problem space is defined by N interdependent features which, for simplicity and without loss of generality, can assume only two states, labelled 0 and 1. The set of features comprising the problem space consists of $\aleph = \{x_1, x_2, \ldots, x_N\}$, with $x_i \in \{0, 1\}$. A particular configuration, that is a possible solution to the problem, is a string $x^i = x^i_1 x^i_2 \ldots x^i_N$. The set of configurations is characterized as: $X = \{x^1, x^2, \ldots, x^{2^N}\}$. The value, or fitness function, consists of a mapping from the set of configurations to the positive real numbers: $V : X \to \Re^+$. A problem is therefore defined by the couple (X, V).

As the size of the set of configurations is exponential in the number of components, whenever the latter is large enough, the state space of problem becomes much too vast to be extensively searched by agents with bounded computational capabilities. One way of reducing its size it to decompose[1] it into sub-spaces. Let $\Im = \{1, 2, \ldots, N\}$ be the set of indexes, and let a **block** $d_i \subseteq \Im$ be a non-empty subset of this set, and let $\mid d_i \mid$ be the **size of block** d_i, i.e. its cardinality.

We define a **decomposition scheme** (or simply **decomposition**) of the space $\aleph$ as a set of blocks:

$$D = \{d_1, d_2, \ldots, d_k\} \text{ such that } \bigcup_{i=1}^{k} d_i = \Im$$

Note that a decomposition does not have necessarily to be a partition; that is, there may be some overlap among the particular decompositions d_i.

Decompositions structure the nature of the organization's search process. Search for alternative basis of action does not take place on a holistic, system-wide basis but tends to be local and to approach different facets of the problem in a sequential manner (Cyert and March 1956). In this spirit, a new configuration is generated and tested by picking a block $d_j \in D$ at random and some (at least one and up to all) components in this block (and only in this block) are mutated, obtaining a new configuration x^h which may differ from the original configuration x^i only in those components belonging to block d_i. If $V(x^h) \geq V(x^i)$, then x^h is retained and becomes the new current configuration; otherwise, x^h is discarded and x^i continues to be the current configuration.

We say that a decomposition scheme D^* is an optimal decomposition of the problem if multiple iterations of this search procedure are always able (after repeated random mutations) to locate the globally optimal configuration(s), starting from any initial configurations. That is, the scheme is such that there is no lock-in into suboptimal configurations. In general, there are many optimal decomposition[2]. For instance, if D^* is an optimal decompositions, all decompositions which can be obtained by the union of some of its blocks will also be optimal decomposition. However, among the set of decompositions satisfying this criterion, we are particularly interested in the finest optimal decomposition(s), i.e. the one(s) whose blocks have minimal cardinality. Blocks in the finest optimal decompositions represent the smallest sub-problems into which the overall problem can be decomposed and still be optimally solved.

We can classify problems in terms of their finest optimal decomposition. In particular, the following types will be widely referred to in our subsequent

[1] A decomposition can be considered as a special case of a search heuristic. Search heuristics are in fact ways of reducing the number of configurations to be considered in a search process.

[2] See Marengo (2000) for a more formal and detailed account of the properties of optimal and sub-optimal decompositions and for an algorithmic procedure which computes them.

analysis:

1. Non-decomposable problem, for which the finest optimal decomposition is the degenerate one: $D^* = \{1, 2, \ldots, N\}$

2. Nearly-decomposable problems (Simon 1981) whose finest optimal decomposition is made of non-disjoint (partially overlapping) blocks, for instance: $D^* = \{1, 2, 3, 4\}, \{3, 4, 5, 6\}, \{5, 6, 7, 8\}\}$

3. Decomposable problems, whose optimal decomposition is made only of disjoint blocks. Furthermore, this decomposition of disjoint blocks can be:

    - coarse, if blocks are not all singletons
    - fine, if all blocks are singletons

Only in this last case is the problem "simple" and optimally solvable through N separate local search processes.

2.2 Organizational Problem-Solving

To this point, we have characterized the problem environment, we now turn our attention to the characterization of the process of organizational search. Organizational search is viewed as being a mix of off-line, cognitive processes and on-line, experiential search (Gavetti and Levinthal 2000). In this spirit, we distinguish two activities within the organization: **cognition** and **action**.

Cognition consists of two facets. One is a belief about the appropriate decomposition of the problem-space, which we denote by Δ^C:

$$\Delta^C = \{\delta_1, \delta_2, \ldots, \delta_h\} \text{ such that } \bigcup_{i=1}^{h} \delta_i = \Im$$

In general, we assume that the organization does not know the correct structure of interdependencies of the problem space (that is $\Delta^C \neq D^*$).

The conjectural decomposition of the problem space is a sort of template that forms the basis for generating new tentative configurations. These tentative configurations comprise the second facet of the belief structure over the relative value of different sets of behaviors. More precisely, the organization specifies a configuration, i.e. binary string of length N that specifies a target solution.

The two elements of cognition interact in the following manner. A block δ_i is selected at random. Some, at least one and up to all, randomly selected features belonging to δ_i are mutated. Thus, how the target strategy varies over time is constrained by the structure of the decomposition. This re-specification of the target strategy occurs every t^C periods. The initial cognition string is randomly generated.

The actual behavior of the organization need not correspond to this target policy string – what we at times have referred to as its strategy. Action, as well as the target, is comprised of a binary string of length[3] N. The organization adapts its behavior towards the target policy string. However, this adaptive process is constrained by the decomposition of action, or more traditionally expressed, the division of labor within the organization. Responsibility for action is decomposed in the following manner:

$$\Theta^C = \{\theta_1, \theta_2, \ldots, \theta_g\} \text{ such that } \bigcup_{i=1}^{g} \theta_i = \Im$$

This decomposition describes the division of labor within the organization (each block can be thought of as a department or production team). The decomposition defines the units whereby operations are coordinated in order to achieve the target set by the cognitive schema.

We assume that the cognition string sets a target sub-string for each action block θ_i as the most preferred pattern of action for such a block. All other possible sub-strings for that block will be randomly ranked [4]. So, for instance, assume that 0110100 is the current target string and that the action decomposition is: $\Theta^A = \{\{1, 2, 3\}, \{4, 5\}, \{6, 7\}\}$. Consider now block $\{1, 2, 3\}$: its target is to produce string 011 and this will be the most preferred string, whereas all the other $2^3 - 1$ strings will be randomly ranked.

Search in the space of actions proceeds according to the following mechanism:

- a block θ_i is selected at random
- some (at least one and up to all) randomly selected bits belonging to θ_i are mutated
- if the new sub-string has higher ranking it is retained, otherwise it is discarded and the initial one is retained

[3] It would be interesting to examine a structure in which the target is of lower-dimensionality than the actual behavior. This reduced dimensionality of the target would pose additional complexities in the mapping from behavior and progress towards the target state.

[4] This structure results in a difficult search space over the set of possible actions as movement towards the target need not be rewarded. At the other extreme, one might specify a reward that is decreasing in the Hamming distance between the actual behavior and the reward. Such a reward structure would make the problem of searching for behavior that achieves the target trivial. Any intermediate structure of reward essentially requires developing fuller cognitive theory on the part of the higher-order actors specifying what constitutes progress towards the target. We assume that the ability to engage in such theorizing is limited and, for simplicity, postulate a random reward for policies that differ from the target.

This sequence is carried out each period[5].

The search for an appropriate action sequence and a desired target strategy interacts in the following manner. Given the cognitive decomposition, a target strategy is specified, x^i_C. This strategy is held fixed for t^C periods. During this interval, the organization searches the space of possible action so as to match the target strategy. Let us call x^i_A the action string that is the outcome of such adaptation and let $V(x^i_A)$ be its value. Now, a new target configuration x^h_C is generated and left unchanged for the following t^C iterations, after which a new action string x^i_A of value $V(x^h_A)$ will emerge. If $V(x^h_A) \geq V(x^i_A)$, then x^h_C will be kept as the current configuration, otherwise it will be discarded and x^i_C will become the new configuration.

A key element of this structure is that the target policy does not receive any direct feed-back from the environment, but only through its, possibly incomplete, implementation through action. As a result, the value attributed to a target policy string may differ from its "true" value. Such discrepancies are more likely when the division of labor at the action level is coarser; a coarser division of labor accentuates the problem of matching the target string with actual behavior. However, as we see in the subsequent analysis, the discrepancy between strategy and action that results may compensate for incorrect cognitive decompositions and help the organization avoid low-level equilibria that may be associated with incorrect cognitions. At the same time, coarser decompositions of labor slow the speed of adapting behavior to the target and in the case of more correct cognitive representations or finer-grained actual problem environments may inhibit overall organizational adaptation.

3 Results

3.1 Decomposable Problem Environments

To develop some initial intuition for this structure, we consider the setting in which the true problem environment is perfectly decomposable. In particular, we consider an environment with $N = 15$ dimensions and specify the environment to be made of three separate blocks of five dimensions each:

$$D^* = \{\{1, 2, 3, 4, 5\}, \{6, 7, 8, 9, 10\}, \{11, 12, 13, 14, 15\}\}$$

. In characterizing the results, we present in our graphs average fitness values over 100 simulation with different random generator seeds, and we normalize such values as deviations from the global optimum (set equal to 1). We explore the impact of different decompositions of cognition "C" and labor "A"

[5] We assume that the pace of adaptation for the action is in general faster than that for cognition, which undergoes mutations every $t^C > 1$ iterations. In addition to its plausibility, this difference is also necessary in order to let action adjust, though possibly imperfectly, to the target before changing the target itself.

for a given environment. Figure 1 reports the results under these different structures, the number associated with the letter C and A indicate how many blocks comprise the decomposition. Thus, C3 implies that the cognitive decomposition consists of 3 blocks of 5 elements each such that[6]:

$$\Delta^C = \{\{1,2,3,4,5\},\{6,7,8,9,10\},\{11,12,13,14,15\}\}$$

Along the same lines, the label A15 indicates that the decomposition of labor consists of 15 blocks of one element each, the finest decomposition possible, that is:

$$\Theta^A = \{\{1\},\{2\},\{3\},.,\{15\}\}$$

i.e. each dimension is treated as independent from the others.

INSERT FIGURE 1 ABOUT HERE

Figure 1 shows that the global optimum is reached by an organization whose cognition is based upon the right decomposition and has the finest possible division of labor at the action level. This is easily explained because when the cognition has the right decomposition and is therefore capable of climbing to the global optimum, then it is more efficient to maximize the division of labor at the action level because in this way targets set by cognition are more promptly and correctly achieved. If instead the cognition is still based upon the correct decomposition but action upon a coarser decomposition, then adaptation of action to cognition is slower. This implies that since cognition's fitness is not observable and learning about the appropriateness of the cognition is driven by fitness of the actions, if the actions are imperfectly adapted to cognition then the value of good cognitions may not be recognized. This observation explains why C3 A3 results in a poorer performance than C3 A15, even though the former provides the "correct" decomposition for action as well as for cognition[7].

Obviously, there is no reason to presume that the organization can identify the correct cognitive decomposition. An interesting question then becomes whether there is an asymmetry between over and under specified decompositions and how errors in cognitive decomposition affect the value of alternative decompositions of action. There are a couple of forces at work underlying the

[6]For simplicity, we assume that the sequencing of elements is correct, that is in numerical order, but that the bracketing of these sequences may be misspecified. This allows us to represent the degree of misspecification purely as a function of the fineness or coarseness of the decomposition, without having to consider the large possible combinations of possible sequencing of the individual policy choices.

[7]This latter problem of coarser action decomposition can be reduced by allowing longer time for action to adapt to cognition, i.e. by reducing the frequency at which cognition is updated. This, however, of course would cause a decrease in the speed of the overall adaptation of the organization.

answer to these questions. First, narrow decompositions of the task structure lead to relatively rapid adaptation of the action string to the firm's espoused strategy. When the cognitive decomposition is broken up more finely than the true problem structure, there is a danger of the organization converging on a low-level equilibrium in the space of possible cognitions. Under such a setting, deviations from the target strategy with respect to a single sub-set of the decomposition may yield inferior results even though a different target may provide the opportunity for higher performance. A decomposition of action that is finer than the decomposition of the cognitive representation will not create an opportunity for broader learning about the set of possible cognitions. A coarser grained task structure effectively creates a link among elements that lie in distinct sub-sets of the cognitive decomposition. These links facilitate broader learning about the space of possible cognitions. Even though the cognitive substring may only consist of three elements, if the task substructures comprise, say 5 elements, than the payoff to matching one subset of the task structure to the cognition potentially reflects the value of 5 elements of the cognitive representation.

There is a second way in which a more coarse-grained task structure may compensate for a overly narrow cognitive representation. The finer than correct decomposition at the cognitive level tend to be trapped into local optima. If action quickly adapts to the target set by cognition, then the entire organization will quickly lock into such local optima due to incorrect cognitive representations. On the contrary, if adaptation at the action level is slower and less precise, then these traps can be avoided. Cognition does not directly receive a payoff signal, but only through the mediation of action implementation;, if this implementation is imperfect (i.e. actions differ from targets), then it may happen that an inferior cognition receives a higher payoff and therefore an (local) optimum may not be perceived as such. Of course, there are diminishing returns to introducing such gaps between action and cognition. If we were to maintain the false cognition represented by C5, but shift the action partition from A5 to A1, learning about alternative strategies is impeded and the rate of adaptation, correspondingly slowed.

3.2 Nearly Decomposable Problem Environments

We now consider, what Simon (1981) suggests is perhaps the more common problem environment, one that is nearly, but not fully decomposable. We consider a nearly decomposable environment of size n=16 made of partially overlapping blocks. The finest optimal decomposition is the following:

$$D^* = \{\{1, 2, 3, 4, 5\}, \{4, 5, 6, 7, 8\}, \{9, 10, 11, 12, 13\}, \{12, 13, 14, 15, 16\}\}$$

where bits 4,5,12,13 are in common between two blocks. The peculiarity of this kind of environment is that it is apparently decomposable only into two blocks of size eight each; however, the structure may actually be more efficiently searched by a finer decomposition which exploits the presence of interface bits (bits 4, 5 and 12,13 respectively) which are common to two otherwise separable blocks. In fact, the two decompositions:

$$\Delta^C = \{\{1,2,3,4,5\},\{6,7,8\},\{9,10,11,12,13\},\{14,15,16\}\}$$

$$\Delta^C = \{\{1,2,3\},\{4,5,6,7,8\},\{9,10,11\},\{12,13,14,15,16\}\}$$

can optimally search the landscape. Bits 4,5 and 12,13 have a key role in the search process. Once they are properly adjusted within a block, they allow a reduction of difficulty in the other blocks to which they belong. Moreover, these interface bits which simultaneously belong to more than one block should not be subject to parallel search. Adaptation within block, say $\{1,2,3,4,5\}$, might be disrupted by changes of bits 4 and 5 determined by the parallel search process within block $\{4,5,6,7,8\}$. As a result, interface bits should be assigned only to one block in the correct decomposition[8].

We refer to such cognitive decompositions as being "modular", because they exploit the distinction between the interface modules and the otherwise separable modules, which characterizes nearly decomposable systems (Baldwin and Clark 2000) and denote them by Cmod . Figure 2 shows that this modular decomposition of the cognition (Cmod) combined with the finest decomposition of action is the most efficient in solving the problem, whereas search based on a cognitive decomposition of two blocks of size eight also reaches the global optimum. but more slowly (because of its larger size).

The Cmod decomposition is finer-grained than the actual problem structure decomposition. In contrast, decomposing the cognition into two components provides a coarser than actual decomposition. However, both decompositions yield a superior adaptive behavior than a decomposition that shares the same number of partitions as the actual problem structure. In particular, in Figure 2 we also consider the decomposition:

$$C4 = \{\{1,2,3,4\},\{5,6,7,8\},\{9,10,11,12\},\{13,14,15,16\}\}$$

. The course grained decomposition of C2 internalizes the interaction among elements 4 and 5 with both subsets 1, 2, and 3, as well as the subset 6, 7, and 8. In contrast, the structure Cmod, partials out the linking policies 3 and 4 and 10 and 11. This allows for the identification of useful cognitions regarding substrings, such as 1, 2, and 3, as well as 6, 7, and 8 conditional on given values for policies 3 and 4. In this manner, the modular structure allows for

[8]Another possible way of managing the interface bits is by hierarchical control, which in turn can take the form of veto power (Dosi et al. (forthcoming); Rivkin and Siggelkow (2002)) by which mutations within block $\{4,5,6,7,8\}$ are stopped if they decrease the fitness value for block $\{1,2,3,4,5\}$, or by direct superordinate control of the interface bits, which cannot be freely mutated by individual blocks.

more effective adaptation than the C4 structure where the implications of a cognition for 1, 2, 3, 4 will be contingent upon the cognition for policy 5 which lies in a distinct partition of the decomposition.

INSERT FIGURE 2 ABOUT HERE

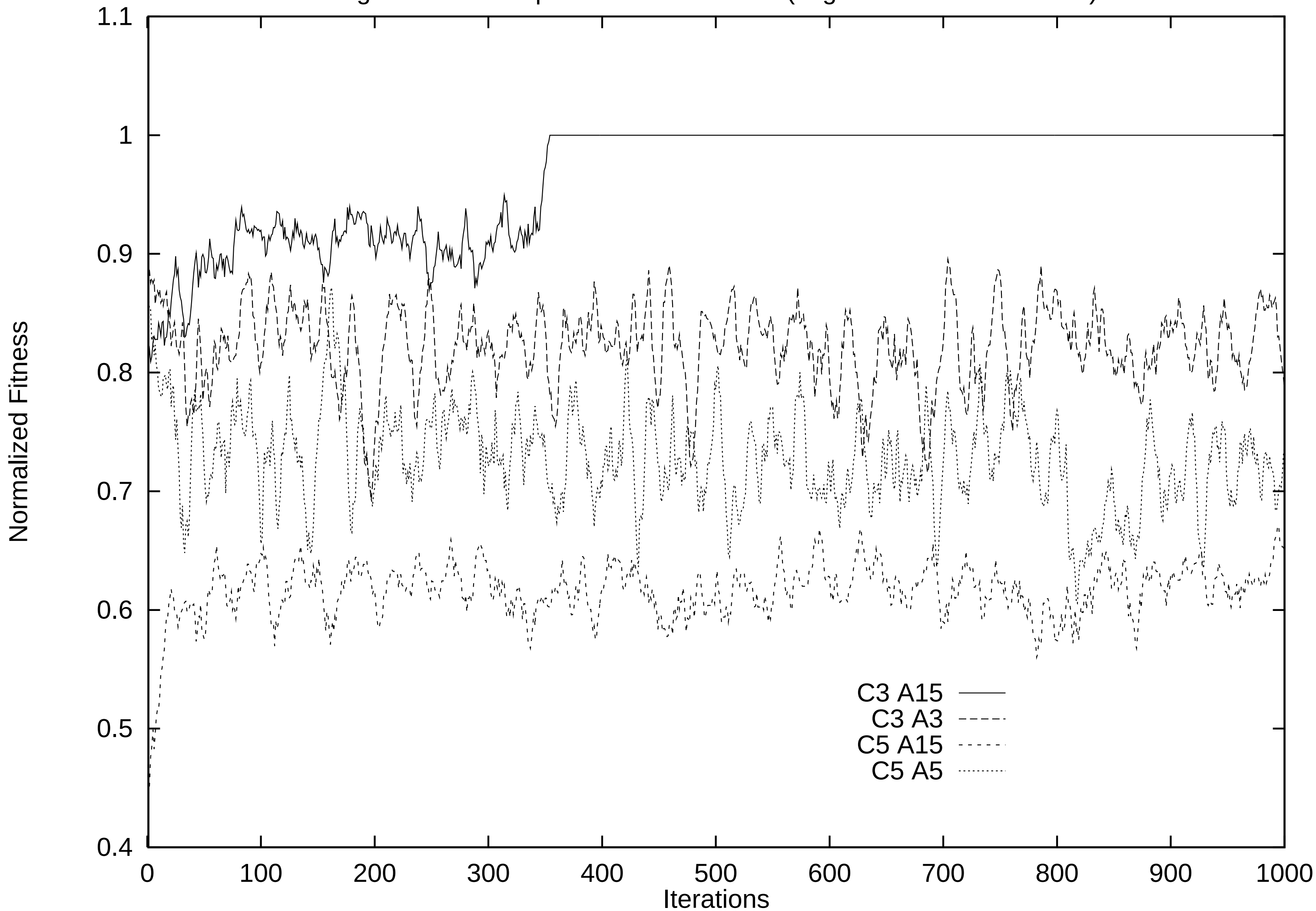
4 Conclusions

One of the most fundamental facts about organizations is that they provide some form of hierarchy. As Simon (1981) has suggested, hierarchy is a common feature of adaptive systems. Hierarchy is present not simply in the form of authority structures but, as Cohen et al. (1996) argue, is present in the nested structure of routine behavior. At the apex of this set of routinized behavior lies broad heuristics. In our modelling efforts here, we start with the fundamental heuristic of how actors conceptualize their environment. How do they dimensionalize their problem spaces? Are individual components of choice considered a distinct dimension or are these components grouped into more aggregate clusters. Given some structure to the decomposition of the problem space, some articulation of intended or desired action must be specified. Beliefs about the desirability of a particular course of action, we term a cognition or a strategy. Finally, how are lower level actors motivated and guided to realize such articulate strategies?

In a very stylized manner, we provide a particular representation of this hierarchy of representation, cognition, and action. This structure allows us to begin to explore the interactions among these levels. We find that distortions in one level, of excessive or under decomposition, may be compensated for by opposite distortions at lower levels. In addition, narrow decompositions of the task structure yield rapid adaptation of action to cognitions. However, in settings in which the representation is ill-specified, such rapid adaptation is likely to lead to a premature lock-in to inferior solutions.

Organizations think and they act. As social scientist we have tended to fallen prey to Descartes mind-body distinction. Neo-classical economics tend to focus exclusively on the mind — explicit choice processes. Behavioral theories, particularly formal models of learning, largely concern themselves with problems of action, and the resulting stimulus-response learning. Real organizations do both. They develop crude belief structures about the world and make choices based on those structures and try to guide action based on those choices. Errors are present at all levels in this process, but so is intentionality. Furthermore, the sequence is not merely linear. Action can influence thinking. As we act in the world, we may be motivated to change our cognitions and possibly even the higher order change of shifts in our representations. While clearly preliminary, the current effort attempts to counter this mind-body divide that tends to permeate our modelling of organizations and to provide a platform for more integrative analysis of organizational behavior.

Figure 1 - Decomposable Environment (avg. over 200 simulations)



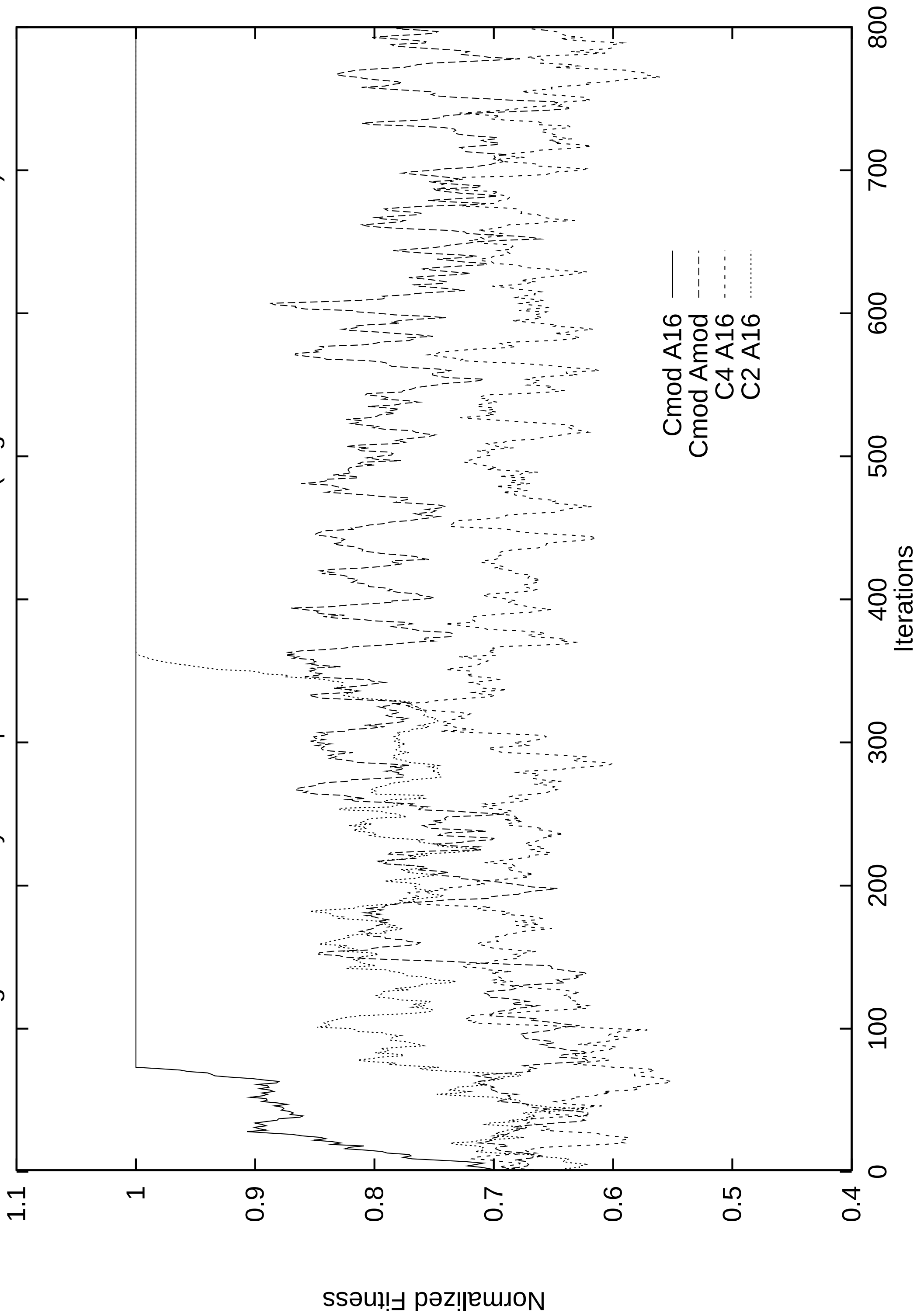


Figure 2 - Nearly-Decomposable Environment (avg. over 200 simulations)

References

BALDWIN, C. Y. and CLARK, K. B. (2000) *Design Rules: The Power of Modularity*, MIT Press, Cambridge, MA.

BURGELMAN, R. A. (1994) "Fading Memories: A Process Theory of Strategic Business Exit in Dynamic Environments", *Administrative Science Quarterly*, **XX** pp. XXX–XXX.

COHEN, M., BURKHART, R., DOSI, G., EGIDI, M., MARENGO, L., WARGLIEN, M. and WINTER, S. (1996) "Routines and Other Recurring Action Patterns of Organizations: Contemporary Research Issues", *Industrial and Corporate Change*, **5** pp. 653–698.

CYERT, R. M. and MARCH, J. G. (1956) *A Behavioral Theory of the Firm*, Prentice Hall, Englewood Cliffs, NJ.

DOSI, G., LEVINTHAL, D. and MARENGO, L. (forthcoming) "Bridging Contested Terrain: Linking Incentive-based and Learning Perspectives on Organizational Evolution", *Industrial and Corporate Change*.

ETHIRAJ, S. and LEVINTHAL, D. (2002) "Modularity and Innovation in Complex Systems", *Academy of Management Best Papers Proceedings*, **XX** pp. XXX–XXX.

GAVETTI, G. and LEVINTHAL, D. (2000) "Looking Forward and Looking Backward: Cognitive and Experimental Search", *Administrative Science Quarterly*, **45** pp. 113–137.

HREBINIAK, L. G. and JOYCE, W. F. (1984) *Implementing Strategy*, MacMillan, London.

KAUFFMAN, S. A. (1993) *The origins of order*, Oxford University Press, Oxford.

LANE, D. (1993) "Artificial worlds and economics: Part I", *Journal of Evolutionary Economics*, **3** pp. 89–107.

LEVINTHAL, D. and WARGLIEN, M. (1999) "Landscape design: Designing for local action in complex worlds", *Organization Science*, **10** pp. 294–321.

MARENGO, L. (2000) "Decentralization and market mechanisms in collective problem-solving", mimeo, University of Teramo.

MARENGO, L., DOSI, G., LEGRENZI, P. and PASQUALI, C. (2000) "The Structure of Problem-solving Knowledge and the Structure of Organizations", *Industrial and Corporate Change*, **9** pp. 757–788.

Michaels, X. (2000) "XXX", *YYY*, **X** pp. XXX–XXX.

Mintzberg, H. (1973) *The Nature of Managerial Work*, Harper and Row, New York.

Nelson, R. and Winter, S. (1982) *An Evolutionary Theory of Economic Change*, Harvard University Press, Cambridge, MA.

Page, S. E. (1996) "Two measures of difficulty", *Economic Theory*, **8** pp. 321–346.

Rivkin, J. and Siggelkow, N. (2002) "Choice Interaction and Organizational Structure", Working paper, Harvard Business School, Cambridge, MA.

Simon, H. A. (1955) "A behavioural model of rational choice", *Quarterly Journal of Economics*, **69** pp. 99–118.

Simon, H. A. (1981) *The sciences of the artificial*, MIT Press, Cambridge, MA, 2nd edition.