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Collective Intelligence and Limited Rationality in the Organization of Ant Colonies and Human Societies*

"Traditional economic theory postulates an 'Economic Man' who in the course of being 'economic' is also 'rational'. This man is assumed to have knowledge of the relevant aspects of his environment which, if not absolutely complete, is at least impressively clear and voluminous. He is assumed also to have a well-organized and stable system of preference and a skill in computation that enables him to calculate, for the alternative courses of action that are available to him, which of these will permit him to reach the highest attainable point on his preference scale."

"Broadly stated, the task is to replace the global rationality of Economic man with a kind of rational behavior that is compatible with the access to information and the computational capacities that are actually possessed by organisms, including man, in the kinds of environments in which such organisms exist."

[From *A Behavioural model of Rational Choice*, by H. A. Simon, 1955]

New insights for understanding complex systems may be obtained by studying ant societies in the light of certain classical theories of organization. These theories suggest that (a) organisms and organizations are capable only of limited rationality, due to the complexity of the environment; (b) classifying such environments is important to understanding the scope of adaptive decision-making; and (c) societies operating in complex environments may usefully resort both to a redundancy of parts (individuals) and a redundancy of functions (behavioural flexibility) to

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promote their survival. These ideas are illustrated by a few diverse examples from ant societies.

I introduced the term Collective Intelligence (Franks 1989) to draw attention to the collective abilities of social insect colonies. Such societies have collective problem-solving and decision-making capabilities beyond the scope of their individual members. The study of adaptive decision-making by animals in their natural environment is known as behavioural ecology. In this article I look at collective intelligence in insect societies in relation to both classical behavioural ecology and general theories of organization and I consider how societies operate in environments where they can exhibit only limited rationality.

Behavioural ecology is concerned with the causes and consequences of decision-making (in its broadest sense) by organisms in their natural environment. It is the general theme of this paper that behavioural ecology should be able to provide insights for the development of artificial life technologies such as robots (or teams of robots) for work in complex and partly unpredictable environments (see for example Deneubourg et al. 1990; 1991).

However, I also suggest that mainstream behavioural ecology, especially as applied to social insects, whilst taking certain insights from human economic theory, has largely missed other equally important insights, namely from the general theory of organisations (see e.g. Morgan 1986), which should enrich both behavioural ecology and studies of artificial complexity.

Many, if not all, of the decision-making systems behavioural ecologists explore are concerned with the organism's choice of alternative patterns of investment of limited resources (including time and energy). Given this preoccupation with resource allocation, it was almost inevitable that behavioural ecologists should turn for inspiration to economic models of investment strategies developed in the humanities. The most obvious example is cost/benefit analyses involving optimization principles. For example, the marginal value theorem was developed as a guideline for investment by firms (see e.g. Intrilligator 1971) — but the same theory can also be applied to calculate the optimal time for organisms to give up foraging in one depletable patch and move on to another in patchy environments (Stephens & Krebs 1986).

The application of economic optimization theory in behavioural ecology has been both extraordinarily successful and rather controversial. It has been successful as a modelling methodology for showing quantitatively some of the huge diversity of sophisticated behavioural adaptations of organisms to their natural (including social and sexual) environments. It is controversial because it can be regarded as bordering on the naive —

appearing to invoke omniscient organisms (or at least an omniscient evolutionary process). This best of all possible worlds is hardly compatible with a long-term view of the evolution as a blind process in which 99 % of all organisms have become extinct (Wilson 1992, p. 192). The strengths and weaknesses of optimization models in behavioural ecology have been debated at considerable length (Oster Wilson 1978, Gould & Lewontin 1979, Stephens & Krebs 1986, Parker & Maynard Smith 1990, Stearns 1992). The heat of this debate, which shows little sign of abating, is only really useful if it causes the protagonists to clarify the issues and, more importantly, if it encourages the exploration of alternative approaches.

The alternative approach of this paper is to explore the ways in which complex environments limit rational decision-making and how societies of organisms are sometimes better at making certain kinds of adaptive decisions than solitary organisms, even though societies also have a limited rationality.

I will begin by briefly reviewing an important body of literature concerning decision-making and the structure and function of organizations that has had relatively little influence on the growth of ideas in behavioural ecology.

The importance of the work of such luminaries as Herbert Simon and Fred Emery for understanding the limitations of patterns of organization in human economic and social systems, which began in the 1940's and 1950's, has been recognized within the humanities (Herbert Simon was awarded the Nobel prize in economics in 1978). Indeed, it continues as a mainstay of many social scientists' approach to the development of management schemes and studies of administration (Morgan 1986). However, I have been able to find rather little evidence of the impact of their ideas in biology (for two brief citations of Simon by behavioural ecologists, see Stephens & Krebs [1986] and Seeley [1989]). This comparative neglect is unfortunate and surprising because Simon and Emery and their colleagues have been particularly concerned with decision-making by individuals or organizations who have access only to limited information in highly complex environments. As such, their work is highly pertinent to behavioural ecology, especially of social organisms whether or not they are natural or artificial life forms.

Limited Rationality as a Consequence of Environmental Heterogeneity

It is all the more surprising that Simon's work has been largely neglected by behavioural ecologists because one of his influential papers (Simon 1956) is centred on a detailed model of a hypothetical organism foraging for food upon which its survival depends. For this reason, I suggest that it is appropriate to recognize Simon as one of the first behavioural ecol-

ogists. However, the fundamental difference between Simon's approach and that of latter day behavioural ecologists is that Simon developed and used his model to show how the decision-making capabilities of organisms (including man) can be just as severely limited by environmental constraints as by behavioural constraints (Simon 1955). It was to emphasize that all economic organizations have limited rationality that Simon (1956) formulated his classic model. (Before detailing this model it is worth recalling that in the 1950's the term behavioural ecology had not yet been coined, indeed two of its founding fathers, Niko Tinbergen and David Lack, were just beginning to provide its foundations [see Krebs & Davies 1987]).

The mathematical model Simon (1956) proposed was simple and elegant, yet it still has some counter-intuitive lessons of value today. Simon imagined an animal inhabiting a flat environment consisting of a network of paths. The organism has a single requirement, food, and engages at any one time in only one of three activities: resting, exploring and eating. Packets of food are rare and they occur at random nodal points in the network of paths. Each food depot is sufficient for one meal. A meal gives the animal the capability to move around the network. It moves and metabolizes at fixed average rates and is able to store a certain amount of food energy, so that it needs to eat at certain average intervals. The organism can perceive a circular portion of its environment, this "vision" enables it to move towards a meal if one lies within its planning horizon. The problem for the organism is to choose its path in such a way that it will not starve.

The organism behaves as follows:

- (1) it explores the network at random looking for a meal:
- (2) when it sees one, it proceeds and eats:
- (3) if the total consumption of energy during the average time required, per meal, for exploration and food-getting is less than the energy of the food consumed in the meal, it can spend the remainder of its time in resting.

Consider that the proportion of nodes in the network where there is food is p , and $0 < p < 1$. An average of d paths lead from each node. The organism can see v moves ahead, that is, it would move through a series of nodes in the network to reach a meal v moves away. H is the maximum number of moves the organisms can make between meals without starving. At any instant, the organism sees d nodes, one move away, d^2 nodes two moves away, and in general, dk nodes k moves away. In all, it can see $d + d^2 + \dots + d^v = (d/d-1)(d^v-1)$ nodes.

When the organism makes one move it sees d' new nodes: m moves

reveal md^v new nodes. The probability, $Q = 1-P$ that it will not survive will be equal to the probability that no feeding positions will be visible in $(H-v)$ moves: this follows because it can make a maximum of H moves, and v of these will be required to reach food it has discovered on its horizon. Because p is small, the possibility that food will be visible inside the organism's planning horizon on the first move can be disregarded.

Let p be the probability that none of the d^v new points visible at the end of a particular move is a food point.

Then:

$$1-P = Q = p^{(H-v)d^v} = (1-p)^{(H-v)d^v} \quad (2)$$

Hence, the probability of this simple organism's survival, from meal to meal, depends on four parameters, two that describe the organism and two the environment: p , the richness of the environment in food; d , the richness of the environment in paths; H , the storage capacity of the organism; and v , the range of vision of the organism.

Simple numerical substitution reveals the relative importance of these parameters. Assume that p is $1/10,000$, $(H-v)$ is 100 , d is 10 , and $v = 3$. Then the probability of seeing a new feeding node after a move is $1 - p = 0.095$. (From equation (1) $p = (1 - 1/10000)^{100}$). The probability of survival P from substituting into equation (2) = 0.9995 . Hence there is in this case only one chance in $10,000$ that the organism will fail to reach a food point before the end of the survival interval. Suppose now that the survival duration $(H-v)$ is increased one-third, that is, from 100 to 133 . The probability of starvation is now reduced to less than one chance in $100,000$. A one-third increase in v (from 3 to 4) has an even greater effect, reducing the probability of starvation from one in 10^4 to one in 10 .

Using the same values, $p = 0.0001$ and $(H-v) = 100$, the probability of survival if the organism behaves completely randomly can be estimated to 0.009 . In this case $P' = [1 - (1-p)^{100}] = 0.009$. In other words, the organism's perceptual powers multiply by a factor of roughly 900 the average speed it takes to find food.

In summary, Simon's (1956) model shows beautifully the relation between the range over which an organism can perceive its environment, its energy storage capacity, and its ability to survive. Simon's (1956) concluding remarks are very revealing:

"Since the organism, like those of the real world, has neither the senses nor the wits to discover an 'optimal' path— even assuming the concept of optimal to be clearly defined — we are concerned only with finding a choice mechan-

ism, that will lead it to pursue a 'satisficing' path, a path that will permit satisfaction at some specified level of all its needs.«

Simon's (1956) suggestion that organisms should suffice rather than optimize has been criticised by Stephens & Krebs (1986). Indeed, given the competitive struggle for existence through evolutionary time, the efficient should replace the merely sufficient, but Simon's major point was, and surely remains true, that the environment is very likely to set many of the limits to rational decision-making and the scope for adaptive responses. For this reason, the technologist's dream of making machines (or teams of machines) with some attributes of social life is always likely to be constrained by environmental complexity. Simon's contemporary, Emery (1967) explored this issue in certain ways that might also be useful in behavioural ecology and artificial life.

The Issue of Environmental Complexity

The reason I have considered Simon's (1956) foraging model in detail is not just for its simplicity and clarity (or because its originality has been overlooked by most behavioural ecologists), but because it helped to support a useful appraisal of environmental complexity by F. Emery (1967). Even more usefully, Emery's analysis in turn leads to some suggestions that I believe are useful in studies of behavioural ecology, especially for students of social insects, and that may, therefore, yield some intriguing insights for artificial life.

F. E. Emery's (1967) Classification of 4 Levels of Environmental Complexity:

1) The Type 1 Environment

This is a placid environment in which there is a random distribution of resources and only one player. It is the environment of Simon's (1956) model organism. Since the resources are randomly distributed and are not dynamic, there is no pattern and nothing to learn. As Emery (1967) points out, in such environments there is no distinction between strategy and tactics.

2) The Type 2 Environment

These environments are more complex but still placid (as in type 1) and there is only one organism or player. But here resources are patterned in space. Hence the organism can have an "optimal" or at least a better than average location. In such environments learning can be useful.

3) The Type 3 Environment

This kind of environment is like that of type 2 except now there is more

than one organism. Such players may compete for limiting resources and best locations. Competitive behaviours and strategies, e. g. territoriality, may play a role in such environments.

"The distributed reactive environment ... A Type 2 environment in which there is more than one system of the same kind, or, to put it another way, where there is more than one system and the environment that is relevant to the survival of one is relevant to the survival of the other."

4) *The Type 4 Environment*

Emery's called his type 4 environments "Turbulent Fields". These are like type 3 but unlike type 1 and 2 because the dynamics come from the environment itself as well as resulting from the dynamics of the players. Good examples of a type 4 environment or turbulent field are mobile growing or declining prey populations, which are dynamic environments for predators. Such turbulent field environments are so complex and predictably unpredictable that management policy is extremely difficult; marine fisheries are a case in point (Allen and McGlade 1987).

The realization that real environments for human organisations and companies are type 4 turbulent fields might explain why the economist's understanding of microeconomics — the theory of the idealized firm — is so complete while understanding of macroeconomics — the overall economic environment — is so incomplete. Similarly, we might understand the foraging strategy of one organism quite well but understand rather poorly the dynamics of the ecological community of which it is a part.

Such a classification of environment types and their effects on limiting rationality, following Simon and Emery, might be useful in itself. Even more useful, however, are Emery's suggestions for ways to cope with turbulent field environments. These are outlined in detail in Emery, so I will consider only a subset of these ideas, those that I consider to be most useful and provocative for understanding ant colonies and potentially for organizing teams of robots. Chief amongst these is the positive role of redundancy in adaptable organizations.

Emery's (1967) first line of reasoning about how organisms may cope with complexity is what I would term "resorting to ignorance". That is, an organism simplifies its turbulent environment by either not sensing or by ignoring its complexity. This may seem trite and trivial — but ignorance is one of the key adaptations in all our lives (cf. Dante's free man *intra due cibi*). Recall the story of the silly ass (a donkey !) which starved to death because it found itself equidistant from two identical piles of equally attractive and nutritious hay (this sophism is often attributed to the 14th century French scholastic philosopher and logician Jean Buridan, but is not found in his works). Death by indecision would be almost infinitely

improbable for a real organism in a natural environment partly because it would be too ignorant to act so stupidly. Ignorance or superficiality are seen by Emery (1967) as the defence of an organization (or an organism), against overly complex environments. Referring to such defences in general he suggests *"they tend to fragment the spatial and temporal connectedness of the larger social systems and focus further adaptive efforts on the localized here and now"*. A good example of adaptive ignorance is the blind leading the blind in army ant raids (see later in this paper).

Emery's second line of reasoning concerns the utility of redundancy. The first clause of the following quote provides a good working definition of artificial life.

"In designing an adaptive self-regulating system one has to have built-in redundancy or else settle for a system with a fixed repertoire of responses that are adaptive only to a finite, strictly identified set of environmental conditions. This is an important property of any system, as an arithmetical increase in redundancy tends to produce a log-increase in reliability. The redundancy may be achieved by having redundant parts but then there must be special control mechanisms (specialized parts) that determine which parts are active or redundant for any particular response. If the control is to be reliable it must also have redundant parts and the question of a further control emerges. In this type of system, reliability is bought at the cost of providing or maintaining the redundant parts, hence the tendency is toward continual reduction of the functions and hence cost of the individual part. The social system of an ant colony relies more upon this principle than does a human system, and a computer more than does an ant colony. The alternative principle is to increase the redundancy of function of the individual parts. This does not entail a pressure toward higher and higher orders of special control mechanisms, but it does entail effective mechanisms within the part for setting and re-setting its functions — for human beings shared values are the most significant of these self-regulating devices. Installing these values of course increases the cost of the parts. The human body is the classic example of this type of system although it is becoming more certain that the brain operates by means of overlapping assemblies based on similar sharing of parts." (Emery 1967, page 230).

Emery above is considering hierarchical control, with a single control unit; our recent research on ants suggests that they have distributed self-organizing control (see Deneubourg et al. 1989, Franks 1989, Franks et al. 1990, 1991, 1992). This interpretation implies that all worker ants are, at least initially, remarkably similar to one another. The problem of having too many middle managers and not enough shop floor workers is over-

come because each ant is its own boss and its own workforce. In this way, the ant society combines the benefits of reliability and flexibility by having both redundant individuals (parts) and individuals with redundant abilities (functions). One natural consequence of examining the mechanisms of ant social cohesion is that we can begin to understand their limited rationality in decision making. The next section of this essay will consider some real-life and theoretical examples of the collective intelligence and limited rationality of ant societies.

Examples of limited rationality, responses to complex environments and solutions through redundancy in ant societies

a) The blind leading the blind

Deneubourg et al. (1989) developed a model, later tested in the field by Franks et al. (1991), which showed literally how the blind could lead the blind in army ant raids. Their model proposed that the huge and complex army ant foraging systems* could be constructed by identical individuals using very simple rules such as "Follow the strongest available pheromone trail and lay your own trail wherever you go". This positive feedback means that traffic attracts traffic. Equally important, ants returning with food from the raid front use the same rules, but lay even more trail on the homeward journey. Hence homebound workers alter the course of outward bound foragers and *vice versa*. In this way the discovery of food has a major influence on the pattern of raiding. Army ant raid patterns read and respond to the foraging environment. Such event-driven or, more correctly, circumstance-driven systems have interesting properties. For example, differing army ants that recognize particular prey with a characteristic spatial distribution will have differing foraging patterns, even though they may have identical communication systems.

But such collective systems have limited rationality. If an army ant colony discovers large packets of prey, such as other ant nests, that are few and far between, it will produce a distributed foraging system consisting of many small sub-swarms. Highly mobile arthropods are unlikely to fall prey to such small swarms because when they jump in a random direction they are unlikely to land back in a swarm and be captured, and hence such potential prey will not influence the raiding pattern. Thus when a colony starts to prey on other ants it is likely to continue to search with small distributed swarms and it will have little ability to switch to other prey. Such collective systems can become locked onto a particular search image. Compare this with a colony that finds many small and frequent prey and

* See Figure 1 on p. 263 in this volume.

so maintains a large, dense, cohesive swarm. Such a colony will continue to capture small mobile arthropods, but it may be able to switch to raiding ant nests. For some colonies, once they have started to read the environment they cannot continue to assess it without prejudice. It seems possible that army ants periodically stop raiding in part to re-initialise their foraging system, allowing them to reconsider the possibilities. Indeed is sleep in general a mechanism for re-booting software ?

b) Selecting the shortest path

In a series of pioneering experiments and models, Goss et al. (1989) and Beckers et al. (1992) have shown that certain ant colonies are able to select the shorter of two paths, even though no single individual has necessarily walked and compared the two routes. This system works like the blind leading the blind through the positive feedback of recruitment communication. Ants that walk the shorter path get there and back sooner, influence their nest mates sooner and so on. Traffic attracts traffic and the longer trail may be completely discarded.

To explore the scope of such collective decision-making, Stickland et al. (1992, 1993) modelled the abstract algorithms of this type of recruitment, including selection of the richer of two food sources either equidistant or asymmetrically located from the colony. They assumed, realistically, that the strength of recruitment can be proportional to resource quality. They were able to show that, depending on the recruitment system, a colony could make a very accurate decision, i.e. choosing with few errors the marginally richer of two food sources, or it could make a rapid decision to concentrate its efforts on one or the other food source. However, there is a trade-off between rapid decision-making and accurate decision making: a recruitment system that makes rapid decisions tends to make inaccurate ones and *vice versa*.

It is possible for a colony to make the wrong decision particularly if (a) it has a small population, (b) foragers leave the nest at infrequent intervals and (c) if each forager has a large influence on the behaviour of its nest-mates. Here a worker may make the longer trip before another one has had an opportunity to make the shorter one. These findings imply that a colony's decision-making is likely to change purely as a function of its population size, even though individuals do not change their communication system. Non-linear systems such as these change their collective behaviour as a function of the number of interacting units. A small group of interacting robots may behave very differently to a large group of interacting units. The problem becomes even more intriguing when different qualities of food are available at different distances. One very important result is that colonies may be completely unable to concentrate their foraging

efforts on a food source that is beyond a certain threshold distance, no matter how rich it is, because a weaker but closer food source will capture all the traffic. In other words, any decision-making system of this kind sets a limit on free exploration (Stickland et al. 1993). Other examples of non-linear decision-making systems in ants may be found in Franks et al. (1990), Hatcher et al. (1992) rhythms and mutual exclusion; Franks & Sendova-Franks (1992) sorting algorithms; Franks et al. (1992) building behaviour; and Tofts & Franks (1992) division of labour.

In conclusion, we should expect societies of people, robots and ants to have limited rationality. In the first attempts to co-ordinate distributed artificial life systems, it seems appropriate to relax the engineer's and certain economist's demands for optimized efficiency and be content with systems that initially suffice. As it is in evolution, optimization can be a distant ideal, but in the technology of artificial life, just as in the blind process of natural selection, the theoretical "best" should not be the enemy of the sufficiently good.

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