Investigating Organizational Strategic Inertia Using a Particle Swarm Model

Anthony Brabazon
Faculty of Commerce
University College Dublin
Ireland
anthony.brabazon@ucd.ie

Arlindo Silva
Instituto Politecnico de Castelo Branco
Av. do Empresario, 6000 Castelo Branco,
Portugal
arlindo@est.ipcb.pt

Tiago Ferra de Sousa
Instituto Politecnico de Castelo Branco
Av. do Empresario, 6000 Castelo Branco
Portugal

Michael O'Neill
Biocomputing & Developmental Systems
University of Limerick
Ireland
michael.oneill@ul.ie

Robin Matthews
Centre for International Business Policy
Kingston University, London
United Kingdom
r.matthews@kingston.ac.uk

Ernesto Costa
Centro de Informatica e Sistemas
da Universidade de Coimbra
Polo II-Pinhal de Marrocos
3030 Coimbra
Portugal
ernesto@dei.uc.pt

***Abstract*— The key task of corporate strategists is to uncover and implement viable strategies for their organization. This is a difficult task for several reasons, including uncertainty as to future payoffs, and strategic inertia. This study, using a swarm metaphor, constructs a simulation model to examine the impact of strategic inertia on the adaptation of the strategic fitness of a population of organizations. The results suggest that a degree of strategic inertia, in the presence of an election operator, can assist rather than hamper adaptive efforts of organizations in static and slowly changing environments.**

I. Introduction

In an organizational setting, a strategy consists of a choice of what activities the organization will perform, and choices as to how these activities will be performed [24]. These choices define the strategic configuration of the organization. Recent work by [20] and [26] has recognized that strategic configurations consist of interlinked individual elements (decisions), and have applied general models of interconnected systems such as Kauffman's NK model to examine the implications of this for processes of organizational adaptation.

Following a long-established metaphor of adaptation as search [29], strategic adaptation is considered in this study as an attempt to uncover peaks on a high-dimensional strategic landscape. Some strategic configurations produce high profits, others produce poor results. The search for good strategic configurations is difficult due to the vast number of strategic configurations possible, uncertainty as to the nature of topology of the strategic landscape faced by an organization, and changes in the topology of this landscape over time. Despite these uncertainties, the search process for good strategies is not blind. Decision-makers receive feedback on the success of their current and historic strategies, and can assess the payoffs received by the strategies of their competitors [18]. Hence, certain areas of the strategic landscape are illuminated.

Organizations do not exist in isolation but interact with, and receive feedback from their environment. Their efforts at strategic adaption are guided by 'social' as well as individual learning. Good ideas discovered by one organization disseminate over time, therefore learning is both individual and social.

Several aspects of swarm systems have attracted the attention of researchers in the social sciences. The essence of these systems is that they exhibit flexibility, robustness and self-organization [4]. Although the systems can exhibit remarkable coordination of activities between individuals, this coordination does not stem from a 'center of control' or a 'directed' intelligence, rather it is self-organizing and emergent. The particle swarm model has been applied to a variety of problems in fields as diverse as engineering [1], chemistry [22] and medicine and psychology [17], but as yet it has not been applied to the domain of organizational science. This paper introduces the model to this domain, and utilizes it to examine the impact of differing degrees of strategic inertia on the adaptive capabilities of a population of organizations.

II. Strategic Adaptation

Strategic adaptation and strategic inertia are closely linked. If strategic adaptation is problematic, inertia is a possible cause. Broadly speaking, this inertia stems from two sources, *imprinting forces*, and as a *consequence of market selection forces*.

Imprinting forces [3] combine to define and solidify the strategic configuration of a newly formed organization. These forces include the dominant initial strategy pursued by the organization, the skills / prior experience of the management team, and the distribution of decision-making influence in the organization at time of founding [3]. All of these influence the initial choice of organizational strategy. As consensus concerning the strategy emerges, it is imprinted on the organization through resource allocation decisions [27]. The imprinting leads to inertia by creating sunk costs, internal political constraints, and a rigid organizational structure. Over time this inertia intensifies due to the formation of an organizational history which creates barriers to industry exit, and legitimacy issues if adaptation is suggested [6]. The resulting inertia serves to circumscribe the organization's ability to adapt its strategy in the future. Imprinting also occurs as relationships are built up with suppliers and customers. The creation of a web of these relationships can serve to constrain the range of strategic alternatives in the future, as strategic moves which dramatically disrupt the web are less likely to be considered.

The discussion of strategic inertia was extended by [7] who posited that inertia is also created as a natural *consequence* of the market-selection process, claiming that 'selection processes tend to favor organizations whose structures are difficult to change.' (p. 149). The basis of this claim is that organizations which can produce a good or service reliably (consistently of a minimum quality standard) are favored for trading purposes by other organizations, and therefore by market selection processes. The routines required to produce a product or service reliably, tend to lead to structural inertia, as the construction of standarized routines leads to an increase in the complexity of the patterns of links between organizational subunits [7], [19]. It can therefore be posited that efficient organizations are likely to exhibit inertia. As organizations seek better environment-structure congruence, their systems become increasingly specialized and interlinked, making changes to their activities become costly and difficult. Tushman and O'Reilly [28] note that structural inertia is rooted in the size, complexity and interdependence of the firm's structures, systems, procedures and processes. Theoretical support for these assertions, that increasing organizational complexity can make adaptation difficult, is found in [11] and [26], as the heightened degree of interconnections between activities within the organization will increase the 'ruggedness' of the strategic landscape on which they are adapting.

III. Particle Swarm Algorithm

This section provides an introduction to the basic Particle Swarm algorithm (PSA).[1] A fuller description of this algorithm and the cultural model which inspired it is provided in [13], [17].

Under the swarm metaphor, a swarm of particles (entities) are assumed to move (fly) through an n-dimensional space, typically looking for a function optimum. Each particle is assumed to have two associated properties, a current position and a velocity. Each particle also has a memory of the best location in the search space that it has found so far (*pbest*), and knows the location of the best location found to date by all the particles in the population (*gbest*). At each step of the algorithm, particles are displaced from their current position by applying a velocity vector to them. The size and direction of this velocity is influenced by the velocity in the previous iteration of the algorithm (simulates 'momentum'), and the current location of a particle relative to its pbest and gbest. Therefore, at each step, the size and direction of each particle's move is a function of its own history (experience), and the social influence of its peer group. A number of variants of the PSA exist. The following paragraphs provide a description of the continuous version of the algorithm [17]. The algorithm is initially described narratively. This is followed by a description of the particle position-update equations.

i. Initialize each particle in the population by randomly selecting values for its location and velocity vectors
ii. Calculate the fitness value of each particle. If the current fitness value for a particle is greater than the best fitness value found for the particle so far, then revise *pbest*
iii. Determine the location of the particle with the highest fitness and revise *gbest* if necessary
iv. For each particle, calculate its velocity according to equation (1)
v. Update the location of each particle
vi. Repeat steps ii - v until stopping criteria are met

Each particle i has an associated current position in d-dimensional space $\mathbf{x_i}$, a current velocity $\mathbf{v_i}$, and a personal best position $\mathbf{y_i}$. During each iteration of the algorithm, the location and velocity of each particle is updated using equations (1) - (4). Assuming a function f is to be maximized, that the swarm consists of n particles, and that r_1, r_2 are drawn from a uniform distribution in the range (0,1), the velocity update is described as follows

$$\mathbf{v_i}(t+1) = \Upsilon(W\mathbf{v_i}(t) + c_1 r_1(\mathbf{y_i} - \mathbf{x_i}(t)) + c_2 r_2(\hat{\mathbf{y}} - \mathbf{x_i}(t))) \quad (1)$$

where $\hat{\mathbf{y}}$ is the location of the global-best solution found by all the particles. A variant on the basic algorithm is to use a local rather than a global version of gbest. In the local version, gbest is set independently for each particle, based on the best point found thus far within a *neighborhood* of that particle's current location. In every iteration of the algorithm, each particle's velocity is stochastically accelerated towards its previous best position and towards a neighborhood (or global) best position. The weight-coefficients c_1 and c_2 control the relative impact of pbest and gbest locations on the velocity of a particle. The parameters r_1 and r_2 ensure that the algorithm is stochastic. A practical affect of the random coefficients r_1 and r_2, is that neither the individual nor the social learning terms are always dominant. Sometimes one or the other will dominate [17].

Although the velocity update has a stochastic component, the search process is not random. It is guided by the memory of past 'good' solutions (corresponding to a psychological tendency for individuals to repeat strategies which have worked for them in the past [15], and by the global best solution found by all particles thus far. W represents a momentum coefficient which controls the impact of a particle's prior-period velocity on its current-period velocity. Each component (dimension) of the velocity vector $\mathbf{v_i}$ is restricted to a range $[-v_{max}, v_{max}]$ to ensure that individual particles do not leave the search space. The implementation of a v_{max} parameter can also be interpreted as simulating the incremental nature of most learning processes [15]. The value of v_{max} is usually chosen

[1] The term PSA is used in place of PSO (Particle Swarm Optimization) in this paper, as the object is not to develop a tool for 'optimizing', but to adapt and apply the swarm metaphor as a model of organizational adaptation.

to be $k * x_{max}$, where $0 < k < 1$. Υ represents a ‘constriction coefficient’ which reduces in value during iterations of the algorithm. This ensures that particles tend to converge over time, as the amplitude of their oscillations (caused by the velocity equation) decreases [17]. Once the velocity update for particle i is determined, its position is updated and pbest is updated if necessary, as described in equations 2-4.

$$\mathbf{x_i}(t+1)=\mathbf{x_i}(t)+\mathbf{v_i}(t+1) \tag{2}$$

$$\mathbf{y_i}(t+1)=\mathbf{y_i}(\mathbf{t}) \text{ if, } f(\mathbf{x_i}(t))\leq f(\mathbf{y_i}(t)), \tag{3}$$

$$\mathbf{y_i}(t+1)=\mathbf{x_i}(t) \text{ if, } f(\mathbf{x_i}(t))>f(\mathbf{y_i}(t)) \tag{4}$$

After all particles have been updated, a check is made to determine whether gbest needs to be updated.

$$\hat{\mathbf{y}}\in(\mathbf{y_0},\mathbf{y_1},...,\mathbf{y_n})|f(\hat{\mathbf{y}})= \max\ (f(\mathbf{y_0}),f(\mathbf{y_1}),...,f(\mathbf{y_n})) \tag{5}$$

The PSA has a number of attractions in the context of a simulation-based study. The model has a simple framework, which is relatively easy to program. The algorithm is not computationally expensive, nor does it impose substantial memory requirements. Despite its simplicity, the algorithm is capable of capturing a surprising level of complexity, as individual particles are capable of both individual and social learning. Learning is ‘distributed’ and parallel. The mechanisms of the basic Particle Swarm model bear *prima facie* similarities to those of the domain of interest, organizational adaptation. It embeds the concept of a population of entities which are capable of individual and social learning. However, the model requires modification before it can employed as a plausible model of organizational adaptation.

IV. Simulation Model

The two key components of the simulation model, the landscape generator (environment), and the adaption of the basic Particle Swarm algorithm to incorporate the activities and interactions of the agents (organizations) are described next.

A. Strategic Landscape

In this study, the strategic landscape is defined using the NK model [10], [11]. It is noted *ab initio* that application of the NK model to define a strategic landscape is not atypical and has support from prior literature in organizational science which has adopted this approach [20], [26], [8], [25], and related work on technological innovation [21], [12]. The NK model considers the behavior of systems which are comprised of a configuration (string) of N individual elements. Each of these elements are in turn interconnected to K other of the N elements (K<N). In a general description of such systems, each of the N elements can assume a finite number of states. If the number of states for each element is constant (S), the space of all possible configurations has N dimensions, and contains a total of $\prod_{i=1}^{N} S_i$ possible configurations.

In Kauffman’s operationalization of this general framework [11], the number of states for each element is restricted to two (0 or 1). Therefore the configuration of N elements can be represented as a binary string . The parameter K, determines the degree of fitness interconnectedness of each of the N elements and can vary in value from 0 to N-1. In one limiting case where K=0, the contribution of each of the N elements to the overall fitness value (or worth) of the configuration are independent of each other. As K increases, this mapping becomes more complex, until at the upper limit when K=N-1, the fitness contribution of any of the N elements depends both on its own state, and the simultaneous states of all the other N-1 elements, describing a fully-connected graph.
If we let s_i represent the state of an individual element i, the contribution of this element (f_i) to the overall fitness (F) of the entire configuration is given by $f_i(s_i)$ when K=0. When K>0, the contribution of an individual element to overall fitness, depends both on its state, and the states of K other elements to which it is linked ($f_i(s_i : s_{i1}, ..., s_{ik})$). A random fitness function (U(0,1)) is adopted, and the overall fitness of each configuration is calculated as the average of the fitness values of each of its individual elements.

Altering the value of K affects the ruggedness of the described landscape, and consequently impacts on the difficulty of search on this landscape [10], [11]. The strength of the NK model in the context of this study is that by tuning the value of K it can be used to generate strategic landscapes (graphs) of differing degrees of local-fitness correlation (ruggedness).

The strategy of an organization is characterized as consisting of N attributes [20]. Each of these attributes represents a strategic decision or policy choice, that an organization faces. Hence a specific strategic configuration $\mathbf{s}$, is represented as a vector $s_1, ..., s_N$ where each attribute can assume a value of 0 or 1 [26]. The vector of attributes represents an entire organizational form, hence it embeds a choice of markets, products, method of competing in a chosen market, and method of internally structuring the organization [26]. Good consistent sets of strategic decisions - configurations, correspond to peaks on the strategic landscape.

The definition of an organization as a vector of strategic attributes finds resonance in the work of Porter [23], [24], where organizations are conceptualized as a series of activities forming a value-chain. The choice of what activities to perform, and subsequent decisions as to how to perform these activities, defines the strategy of the organization. The individual attributes of an organization’s strategy interact. For example, the value of an efficient manufacturing process is enhanced when combined with a high-quality sales force. Differing values for K correspond to varying degrees of payoff-interaction among elements of the organization’s strategy [26]. As K increases, the difficulty of the task facing strategic decision makers is magnified. Local-search attempts to improve an organization’s position on the strategic landscape become ensnared in a web of conflicting constraints.

It is acknowledged that there are limitations to using the NK model as a strategic landscape generator. The model produces a finite graph and presupposes the existence of a 'strategy' space, albeit one which may be poorly understood by strategists. It is also noted that the NK model assumes a constant value of K for all elements. In reality, the value of K is likely to differ for varying elements of a strategy vector. In the work of [25], a distinction is drawn between *generic activities* which are likely to have an optimal configuration for many firms, for example, the possession of an accounting system. Generic activities (or 'table-stakes'), whilst important for the successful operation of the firm, are usually not strongly interconnected with the non-generic activities of the firm [25]. In contrast, the firm-specific element of strategy are typically highly interconnected, as they embed choices involving trade-offs between alternative strategic configurations [24], [25]. Hence the NK landscape can be considered to represent these non-generic, interconnected, elements of the strategy vector, rendering the assumption of a constant value of K more plausible.

B. Simulation Model

Five characteristics of the problem domain which impact on the design of a simulation model are:

i. The environment is dynamic
ii. Organizations are prone to strategic inertia, they are 'anchored' by their past
iii. Organizations do not knowingly select poorer strategies than the one they already have (election operator)
iv. Organizations make errorful *ex-ante* and assessments of fitness
v. Organizations co-evolve

In this paper we report results which consider the first three of these factors. Future work will extend this study to incorporate the latter two. We note that this model bears passing resemblance to the 'eleMentals' model of [16], which combined a swarm algorithm and an NK landscape, to investigate the development of culture and intelligence in a population of hypothetical beings called 'eleMentals'. However, the 'strategic' model developed in this study is differentiated from the eleMental model, not just on grounds of application domain, but because of the inclusion of an 'anchor' or inertia term, and also through the investigation of both static and dynamic environments.

1) Dynamic environment: Organizations do not compete in a static environment. The environment may alter as a result of exogenous events, for example a 'regime change' such as the emergence of a new technology, or a change in customer preferences. This can be mimicked in the simulation by stochastically respecifing the strategic landscape during the course of a simulation run. These respecifications simulate a dynamic environment, and a change in the environment may at least partially negate the value of past learning (adaptation) by organizations. Minor respecifications are simulated by altering the fitness values associated with one of the N dimensions in the NK model, whereas in major changes, the fitness of the entire NK landscape is redefined. The environment faced by organizations can also change as a result of competition between the population of organizations. The affect of this competition is left for future work.

2) Anchor: Organizations do not have complete freedom to alter their current strategy. Their adaptive processes are subject to 'conservatism' arising from strategic inertia. This inertia springs from the organization's culture, history, and the mental models of its management [3]. In the simulation, strategic inertia is mimicked by implementing a 'strategic anchor', and the modeler can vary the weight attached to the anchor factor in the simulation from zero to high. In the latter case, the organization is highly constrained from altering its strategic stance. By allowing the weight attached to the anchor to vary, adaptation processes corresponding to different industries, each with different levels of inertia, can be simulated.

Inertia could be incorporated into the PSA in a variety of ways. We have chosen to incorporate it into the velocity update equation, so that the velocity and direction of the particle at each iteration is a function, not just of pbest and gbest, but also the location of its 'strategic anchor'. Therefore for the simulations, equation 1 is altered by adding an additional 'anchor' term

$$\mathbf{v_i}(t{+}1){=}\mathbf{v_i}(t){+}R_1(\mathbf{y_i}{-}\mathbf{x_i}(t)){+}R_2(\hat{\mathbf{y}}{-}\mathbf{x_i}(t){+}R_3(\mathbf{a_i}{-}\mathbf{x_i}(t)) \qquad (6)$$

where $\mathbf{a_i}$ represents the position of the anchor for organization i (a full description of the other terms such as R_1 is provided in the pseudo-code below). The weight attached to the anchor parameter (R_3) (relative to those attached to pbest and gbest), can be altered by the modeler. The position of the anchor can be fixed at the initial position of the particle at the start of the simulation, or it can be allowed to 'drag', thereby being responsive to the adaptive history of the particle. In the latter case, the position of the anchor for each particle corresponds to the position of that particle 'x' iterations ago.

Two other alterations are made to the velocity update equation as originally stated in equation 1. The momentum term W and the constriction coefficient Υ are omitted on the grounds that these factors implicitly embed an inertia component. Including these terms could therefore bias the comparison of populations of organizations operating with/without a strategic anchor.

3) Election operator: Real-world organizations do not usually intentionally move to 'poorer' strategies. Hence, an 'election' operator (also referred to as a *conditional update* or *ratchet operator*) is implemented, which when turned on ensures that position updates which would worsen an organization's strategic fitness are discarded. In these cases, an organization remains at its current location. One economic interpretation of the election operator, is that strategists carry out a mental simulation or 'thought experiment'. If the expected fitness of the new strategy appears unattractive, the 'bad idea' is discarded. In this paper, we assume that organizations can correctly predict the worth of new strategies *ex-ante*. This assumption will be dropped in future work.

4) Outline of algorithm: A number of further modifications to the basic PSA are required. As the strategic landscape is defined using a binary representation, the basic PSA is adapted for the binary case (BinPSO) [14]. The pseudo-code for the algorithm is as follows:

```
For each particle in turn
For each dimension n

v[n]=v[n]+R1*(pb[n]-x[n])+R2*(gb[n]-x[n])+R3*(a[n]-x[n])
If(v[n]>Max) v[n]=Vmax
    If(v[n]<-Vmax) v[n]=-Vmax
    If(Pr<S(v[n]))t[n]=1
    Else t[n]=0
If(fitness(t))>fitness(x))  //conditional move
    For each dimension n
        x[n]=t[n]
UpdateAnchor(a)        //if iteratively update anchor
                       //option is selected
```

$R1$, $R2$ and $R3$ are random weights drawn from the uniform distribution ranging from 0 to $R1_{max}$, $R2_{max}$ and $R3_{max}$ respectively, and they weight the importance attached to the gbest, pbest and anchor in each iteration of the algorithm. $R1_{Max}$, $R2_{Max}$ and $R3_{Max}$ are constrained to sum to 4.0. x is the particle's actual position, pb is its past best position, gb the global best and a is the position of the particle's anchor. V_{max} is set to 4.0. Pr is a probability value drawn from a uniform distribution ranging from 0 to 1, and S is the sigmoid function: $S(x) = \frac{1}{1+exp(-x)}$, which squashes v into a 0 to 1 range. t is a temporary record which is used in order to implement conditional moving. If the new strategy is accepted, t is copied into x, otherwise t is discarded and x remains unchanged.

V. Results

All simulations were run for 5,000 iterations, and all reported fitnesses are the average population fitnesses, and average environment best fitnesses, across 30 separate simulation runs. On each of the simulation runs, the NK landscape is specified anew, and the positions and velocities of particles are randomly initialized at the start of each run. A population of 20 particles is employed, with a neighborhood of size 18. The choice of a high value for the neighborhood, relative to the size of the population, arises from the observation that real-world organizations know the profitability of their competitors.

The tables (I, II, and III) provide the results for each of fourteen distinct PSA 'variants', at the end of 5,000 iterations, across a number of static and dynamic NK landscape 'scenarios'. In each scenario, the same series of simulations are undertaken. Initially, a basic PSA is employed, without an anchor or a ratchet (conditional move) heuristic. This simulates a population of organizations searching a strategic landscape, where the population has no strategic inertia, and where organizations do not utilize a ratchet operator in deciding whether to alter their position on the strategic landscape.

The basic PSA is then supplemented by inclusion of a series of strategic anchor formulations, ranging from an anchor which does not change position during the simulation (initial position anchor) to one which can adapt after a time-lag (moving anchor). Two lag periods are examined, 20 and 50 iterations. Differing weights can be attached to the anchor term in the velocity equation 6, ranging from 0 (anchor is 'turned off') to a maximum of 4. To determine whether the weight factor for the anchor term has a critical impact on the results, results are reported for weight values of both 1 and 3, corresponding to low and high inertia weights. Next, to isolate the effect of the ratchet, the conditional move operator is implemented, and the anchor term is dropped. Finally, to ascertain the combined effect of both ratchet and anchor, the anchor simulations outlined above are repeated with the ratchet operator 'turned on'. 'Real world' strategy vectors consist of a large array of strategic decisions. A value of N=96 was chosen in defining the landscapes in this simulation. It is noted that there is no unique value of N that could have been selected, but the selection of very large values are not feasible due to computational limitations. However, a binary string of 96 bits provides 2^{96}, or approximately 10^{28}, distinct choices of strategy. It is also noted that we would expect the dimensionality of the strategy vector to exceed the number of organizations in the population, hence the size of the population is kept below 96, and a value of 20 is chosen. A series of landscapes of differing K values (0,4 and 10), representing differing degrees of fitness inter-connectivity, were used in the simulations.

A. Static Landscape

Table I and Figures 1 and 2 provide the results for a static NK landscape. Examining these results suggests that the basic PSA, without anchor or ratchet heuristics, performs poorly, even on a static landscape. The average populational fitnesses obtained after 5,000 iterations (averaged over all 30 runs) is no better than random search, suggesting that unfettered adaptive efforts, based on 'social communication' between organizations (gbest), and a memory of good past strategies (pbest) is not sufficient to achieve high levels of populational fitness. When various anchor term mechanisms, simulating strategic inertia, are added to the basic PSA, the results are not qualitatively altered from those of the basic PSA. This suggests that social communication and inertia, are not sufficient for the attainment of high levels of populational strategic fitness.

When a ratchet heuristic is added to the basic PSA, a significant improvement (statistically significant at the 5% level) in both average populational, and average environment best fitness is obtained across landscapes of all K values, suggesting that the simple decision heuristic of 'only abandon your current strategy for a better one' can lead to notable increases in populational fitness.

Finally, the results of a series of simulations which combine anchor and ratchet mechanisms are reported. Virtually all of these combinations lead to significantly (at the 5% level) enhanced levels of populational fitness against the ratchet-only PSA, *suggesting that strategic inertia can be beneficial, when organizations employ a conditional move test before adopting new strategies*. Examining the combined ratchet and anchor results in more detail, the best results are obtained when the anchor is not fixed at the initial location of each particle on the landscape, but when it is allowed to 'drag' or adapt, over time. The results are not qualitatively sensitive to the weight value (1 or 3).

B. Dynamic Landscape

The real world is rarely static, and changes in the environment can trigger adaptive behavior by agents in a system [2]. Two specific scenarios are examined. Table II provides the results for the case where a single dimension of the NK landscape is respecified in each iteration of the algorithm with a probability of P=0.00025. Table III and Figures 3 and 4 provide results for the case where the entire NK landscape is respecified with the same probability. When the landscape is wholly or partially respecified, the benefits of past strategic learning by organizations is eroded (see [5], [9], [2] for a detailed discussion of the utility of the PSO in tracking dynamic environments).

Qualitatively, the results in both scenarios are similar to those obtained on the static landscape. The basic PSA, even if supplemented by an anchor mechanism, does not perform any better than random search. Supplementing the basic PSA with the ratchet mechanism leads to a significant improvement in populational fitness, with a further improvement in fitness occurring when the ratchet is combined with an anchor mechanism. In the latter case, an adaptive or dragging anchor gives better results than a fixed anchor, but the results between differing forms of dragging anchor do not show a clear dominance for any particular form. As for the static landscape case, the results for the combined ratchet / anchor, are relatively insensitive to the choice of weight value (1 or 3).

Algorithm	Fitness (N=96, K=0)	(N=96, K=4)	(N=96, K=10)
Basic PSA	0.4641 (0.5457)	0.5002 (0.6000)	0.4991 (0.6143)
Initial Anchor, w=1	0.4699 (0.5484)	0.4921 (0.5967)	0.4956 (0.6102)
Initial Anchor, w=3	0.4943 (0.5591)	0.4994 (0.5979)	0.4991 (0.6103)
Mov. Anchor (50,1)	0.4688 (0.5500)	0.4960 (0.6003)	0.4983 (0.6145)
Mov. Anchor (50,3)	0.4750 (0.5631)	0.4962 (0.6122)	0.5003 (0.6215)
Mov. Anchor (20,1)	0.4644 (0.5475)	0.4986 (0.6018)	0.5001 (0.6120)
Mov. Anchor (20,3)	0.4677 (0.5492)	0.4994 (0.6156)	0.4994 (0.6229)
Ratchet PSA	0.5756 (0.6021)	0.6896 (0.7143)	0.6789 (0.7035)
Rach-Initial Anchor, w=1	0.6067 (0.6416)	0.6991 (0.7261)	0.6884 (0.7167)
Rach-Initial Anchor, w=3	0.5993 (0.6361)	0.6910 (0.7213)	0.6844 (0.7099)
Rach-Mov. Anchor (50,1)	0.6659 (0.6659)	0.7213 (0.7456)	0.6990 (0.7256)
Rach-Mov. Anchor (50,3)	0.6586 (0.6601)	0.7211 (0.7469)	0.6992 (0.7270)
Rach-Mov. Anchor (20,1)	0.6692 (0.6695)	0.7211 (0.7441)	0.6976 (0.7243)
Rach-Mov. Anchor (20,3)	0.6612 (0.6627)	0.7228 (0.7462)	0.6984 (0.7251)

TABLE I

AVERAGE (ENVIRONMENT BEST) FITNESS AFTER 5,000 ITERATIONS, STATIC LANDSCAPE.

Algorithm	Fitness (N=96, K=0)	(N=96, K=4)	(N=96, K=10)
Basic PSA	0.4667 (0.5245)	0.4987 (0.5915)	0.4955 (0.6065)
Initial Anchor, w=1	0.4658 (0.5293)	0.4908 (0.5840)	0.4957 (0.6038)
Initial Anchor, w=3	0.4922 (0.5513)	0.4992 (0.5953)	0.5001 (0.60852)
Mov. Anchor (50,1)	0.4614 (0.5200)	0.4975 (0.5927)	0.5008 (0.6044)
Mov. Anchor (50,3)	0.4691 (0.5400)	0.4975 (0.6040)	0.4987 (0.6174)
Mov. Anchor (20,1)	0.4686 (0.5315)	0.5010 (0.6002)	0.4958 (0.6099)
Mov. Anchor (20,3)	0.4661(0.5434)	0.4964(0.6084)	0.4988 (0.6137)
Ratchet PSA	0.5783 (0.6056)	0.6859 (0.7096)	0.6808 (0.7066)
Rach-Initial Anchor, w=1	0.6207 (0.6553)	0.6994 (0.7330)	0.6895 (0.7142)
Rach-Initial Anchor, w=3	0.5927 (0.6239)	0.6900 (0.7182)	0.6850 (0.7140)
Rach-Mov. Anchor (50,1)	0.6676 (0.6688)	0.7187 (0.7438)	0.6987 (0.7241)
Rach-Mov. Anchor (50,3)	0.6696 (0.6696)	0.7203 (0.7462)	0.6989 (0.7264)
Rach-Mov. Anchor (20,1)	0.6689 (0.6694)	0.7193 (0.7426)	0.6974 (0.7251)
Rach-Mov. Anchor (20,3)	0.6594 (0.6622)	0.7221 (0.7450)	0.6987 (0.7280)

TABLE II

AVERAGE (ENVIRONMENT BEST) FITNESS AFTER 5,000 ITERATIONS, 1 DIMENSION RESPECIFIED STOCHASTICALLY.

Algorithm	Fitness (N=96, K=0)	(N=96, K=4)	(N=96, K=10)
Basic PSA	0.4761 (0.5428)	0.4886 (0.5891)	0.4961 (0.6019)
Initial Anchor, w=1	0.4819 (0.5524)	0.4883 (0.5822)	0.4982 (0.6075)
Initial Anchor, w=3	0.5021 (0.5623)	0.4967 (0.5931)	0.4998 (0.6047)
Mov. Anchor (50,1)	0.4705 (0.5450)	0.4894 (0.5863)	0.4974 (0.6008)
Mov. Anchor (50,3)	0.4800 (0.5612)	0.4966 (0.6053)	0.5010 (0.6187)
Mov. Anchor (20,1)	0.4757 (0.5520)	0.4926 (0.5867)	0.4985 (0.6097)
Mov. Anchor (20,3)	0.4824 (0.5632)	0.4986 (0.6041)	0.5004 (0.6163)
Ratchet PSA	0.5877 (0.6131)	0.6802 (0.7092)	0.6754 (0.7015)
Rach-Initial Anchor, w=1	0.6187 (0.6508)	0.6874 (0.7180)	0.6764 (0.7070)
Rach-Initial Anchor, w=3	0.6075 (0.6377)	0.6841 (0.7130)	0.6738 (0.7017)
Rach-Mov. Anchor (50,1)	0.6517 (0.6561)	0.7134 (0.7387)	0.6840 (0.7141)
Rach-Mov. Anchor (50,3)	0.6597 (0.6637)	0.7049 (0.7304)	0.6925 (0.7225)
Rach-Mov. Anchor (20,1)	0.6575 (0.6593)	0.7152 (0.7419)	0.6819 (0.7094)
Rach-Mov. Anchor (20,3)	0.6689 (0.6700)	0.7158 (0.7429)	0.6860 (0.7147)

TABLE III

AVERAGE (ENVIRONMENT BEST) FITNESS AFTER 5,000 ITERATIONS, ENTIRE LANDSCAPE RESPECIFIED STOCHASTICALLY.

VI. CONCLUSIONS

In this paper, a synthesis of a strategic landscape defined using the NK model, and a Particle Swarm metaphor is used to model the strategic adaptation of organizations. The results suggest that a degree of strategic inertia, in the presence of an election operator, can assist rather than hamper the adaptive efforts of populations of organizations in static and slowly changing strategic environments. The results also provide an interesting perspective on the claim by [7] that strategic inertia may be a consequence of market-selection processes. The results of this study suggest that there may be good reasons, from a *populational perspective*, for market selection processes to encourage the development of populations of organizations which exhibit a degree of strategic inertia. The results also suggest that despite the claim for the importance of social learning in populations, social learning alone is not always enough, unless learnt lessons can be maintained by means of an election mechanism.

No search heuristic will perform equally on all landscapes and across all scales of environmental change. Hence, we acknowledge that the results of this study will not generalize to all possible forms of landscape, and all rates of environmental change. The effect of gbest, pbest and inertia terms, is to 'pin' each organization to a region of the strategic landscape. To the extent that the entire population of organizations have converged to a relatively small region of the landscape, they may find it impossible to migrate to a new high-fitness region if that region is far away from their current location. This suggests that the benefits of an inertia heuristic for a population of organizations comes at a price, the risk of catastrophic failure of the entire population to adapt to a major change in the strategic landscape. In real-world environments, this is compensated for by the birth of new organizations.

Finally, it is noted that the concept of anchoring developed in this paper is not limited to organizations, but is plausibly a general feature of social systems. Hence, the extension of the

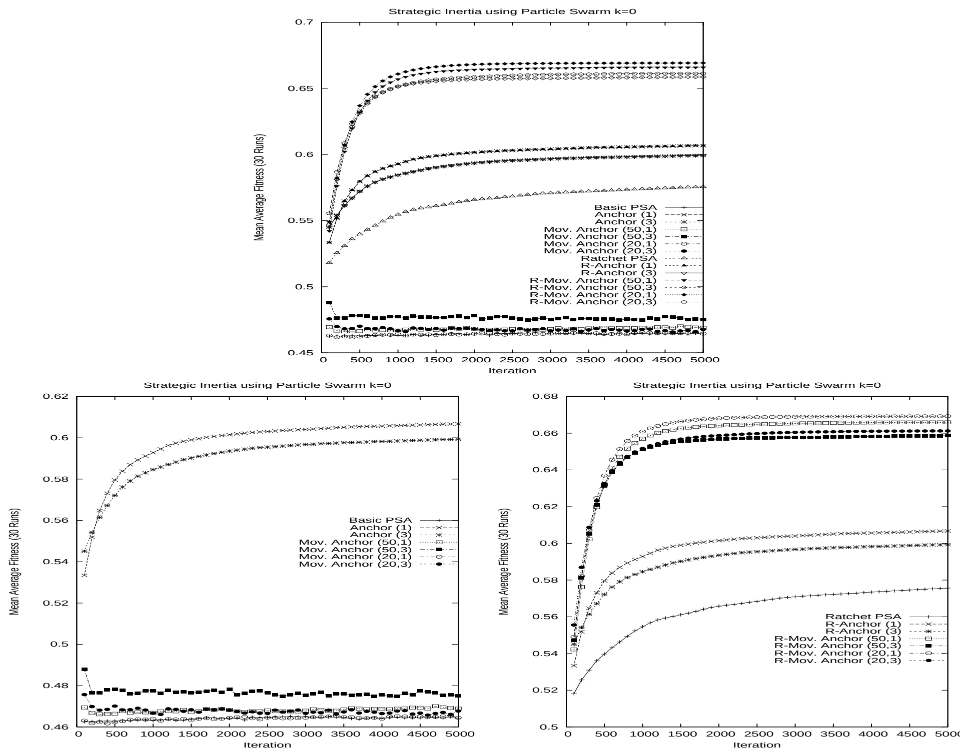

Fig. 1. Plot of the mean average fitness on the static landscape where k=0.

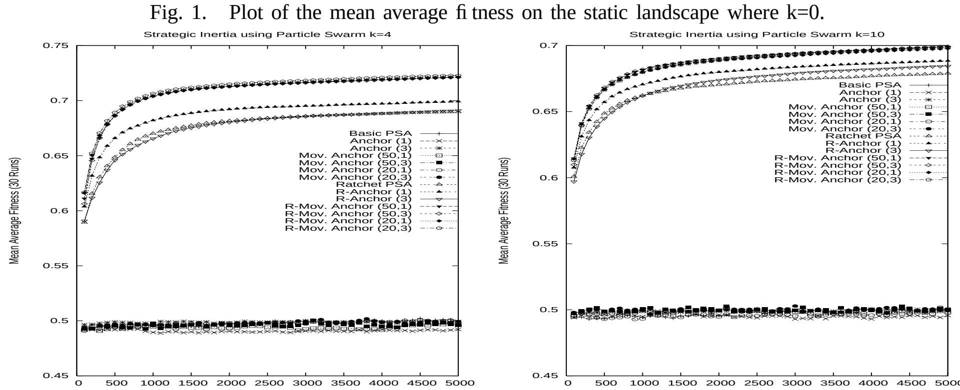

Fig. 2. Plot of the mean average fitness on the static landscape where k=4 (left) and 10 (right).

social swarm model to incorporate inertia may prove useful beyond this study.

REFERENCES

[1] Abido, M. (2002). Optimal power flow using particle swarm optimization, *Electrical power & Energy Systems*, 24:563-571.

[2] Blackwell, T. (2003). Swarms in Dynamic Environments, *Proceedings of GECCO 2003*, Lecture Notes in Computer Science (2723), Springer-Verlag, Berlin, pp. 1-12.

[3] Boeker, W. (1989). Strategic Change: The Effects of Founding and History, *Academy of Management Journal*, 32(3):489-515.

[4] Bonabeau, E., Dorigo, M. and Theraulaz, G. (1999). *Swarm Intelligence: From natural to artificial systems*, Oxford: Oxford University Press.

[5] Eberhart, R. and Shi, Y. (2001). Tracking and optimizing dynamic systems with particle swarms, *in Proceedings of the CEC 2001*, 94-97:IEEE Press.

[6] Hannan, M. and Freeman, J. (1977). The Populational Ecology of Organizations, *American Journal of Sociology*, 82(5): 929-964.

[7] Hannan, M. and Freeman, J. (1984). Structural Inertia and Organizational Change, *American Sociological Review*, 49:149-164.

[8] Gavetti, G. and Levinthal, D. (2000). Looking Forward and Looking Backward: Cognitive and Experiential Search, *Administrative Science Quarterly*, 45:113- 137.

[9] Hu, X. and Eberhart, R. (2002). Adaptive particle swarm optimization: detection and response to dynamic systems, *in Proceedings of CEC 2002*, 1666-1670:IEEE Press.

[10] Kauffman, S. and Levin, S. (1987). Towards a General Theory of Adaptive Walks on Rugged Landscapes, *Journal of Theoretical Biology*, 128:11-45.

[11] Kauffman, S. (1993). *The Origins of Order*, Oxford,England: Oxford University Press.

[12] Kauffman, S., Lobo, J. and MacReady, W. (1998). Optimal Search on a Technology Landscape, *Santa Fe Institute Working Paper 98-10-091*.

[13] Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization, *Proceedings of the IEEE International Conference on Neural Networks*, December 1995, pp.1942-1948.

[14] Kennedy, J. and Eberhart, R. (1997). A discrete binary version of the particle swarm algorithm, *Proceedings of the Conference on Systems, Man and Cybernetics*, pp. 4104-4109:IEEE Press.

[15] Kennedy, J. (1997). The particle swarm: Social adaptation of knowledge,

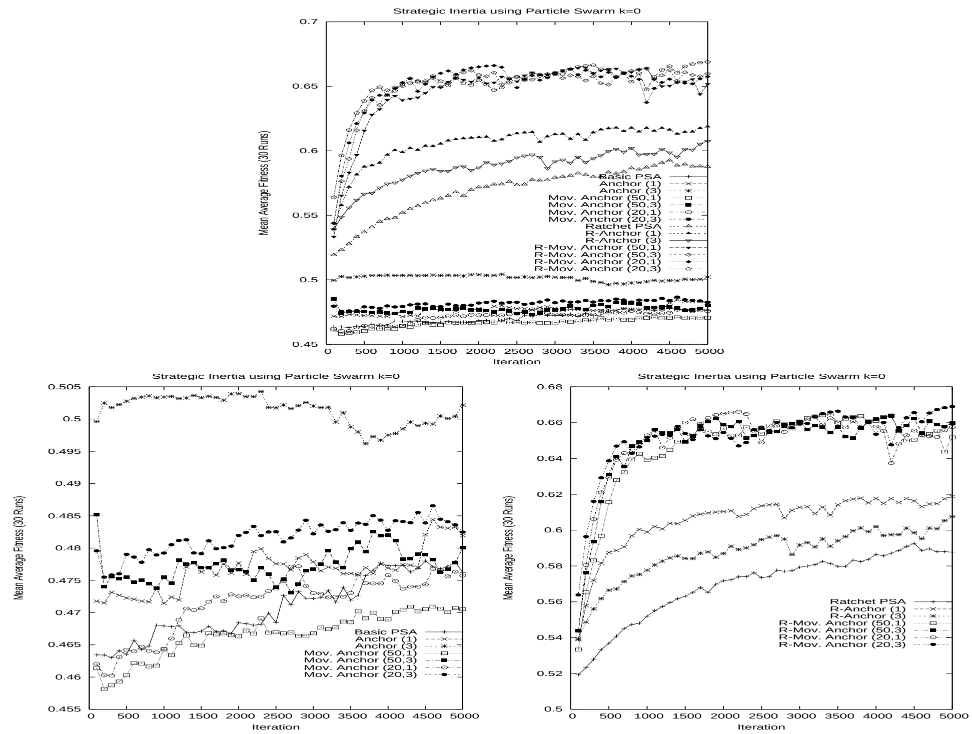

Fig. 3. Plot of the mean average fitness on the dynamic landscape where k=0.

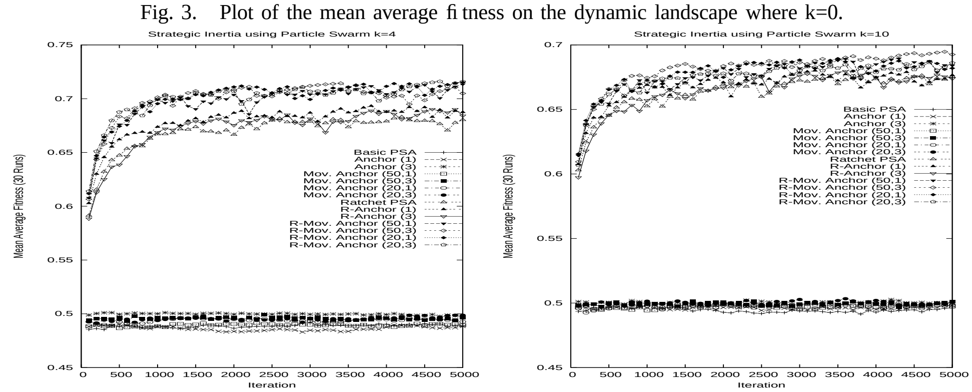

Fig. 4. Plot of the mean average fitness on the dynamic landscape where k=4 (left) and 10 (right).

Proceedings of the International Conference on Evolutionary Computation, pp. 303-308:IEEE Press.

[16] Kennedy, J. (1999). Minds and Cultures: Particle Swam Implications for Beings in Sociocognitive Space, *Adaptive Behavior*, 7(3/4):269-288.

[17] Kennedy, J., Eberhart, R. and Shi, Y. (2001). *Swarm Intelligence*, San Mateo, California: Morgan Kauffman.

[18] Kitts, B., Edvinsson, L. and Beding, T. (2001). Intellectual capital: from intangible assets to fitness landscapes, *Expert Systems with Applications*, 20:35-50.

[19] Levinthal, D. (1991). Random Walks and Organisational Mortality, *Administrative Science Quarterly*, 36:397-420.

[20] Levinthal, D. (1997). Adaptation on Rugged Landscapes, *Management Science*, 43(7):934-950.

[21] Lobo, J. and MacReady, W. (1999). Landscapes: A Natural Extension of Search Theory, *Santa Fe Institute Working Paper 99-05-037*.

[22] Ourique, C., Biscaia, E. and Pinto, J. (2002). The use of particle swarm optimization for dynamical analysis in chemical processes, *Computers and Chemical Engineering*, 26:1783-1793.

[23] Porter, M. (1985). *Competitive Advantage:Creating and Sustaining Superior Performance*, New York, The Free Press.

[24] Porter, M. (1996). What is Strategy?, *Harvard Business Review*, Nov-Dec, 61-78.

[25] Porter, M. and Siggelkow, N. (2001). Contextuality within Activity Systems,*Harvard Business School Working Paper Series*, No. 01-053, 2001.

[26] Rivkin, J. (2000). Imitation of Complex Strategies, *Management Science*, 46(6):824- 844.

[27] Stuart, T. and Podolny, J. (1996). Local Search and the Evolution of Technological Capabilities, *Strategic Management Journal*, 17:21-38.

[28] Tushman, M. and O'Reilly, C. (1996). Ambidextrous Organizations: Managing Evolutionary and Revolutionary Change, *California Management Review*, 38(4):8-30.

[29] Wright, S. (1932). The roles of mutation, inbreeding, crossbreeding and selection in evolution, *Proceedings of the Sixth International Congress on Genetics*, 1:356-366.