

Revue Internationale de

ISSN 0980-1472

systemique

ÉVOLUTION ET APPRENTISSAGE
EN ÉCONOMIE

L'hypothèse Lamarckienne remise en question

Sous la direction d'Ehud ZUSCOVITCH

Vol. 7, N° 5, 1993

afcet

DUNOD

AFSCET

Revue Internationale de
systemique

**Revue
Internationale
de Sytémique**

volume 07, numéro 5, pages 627 - 642, 1993

Evolution strategies:
simple “models” of natural processes?

Franck Kursawe

[Numérisation Afscet, août 2017.](#)



Creative Commons

- R. SELTEN, Reexamination of the perfectness concept for equilibrium points in extensive games, *International Journal of Game Theory*, 4, 1975, p. 25-55.
- J. SWINKELS, Evolutionary stability with equilibrium entrants, mimeo Stanford University, 1990.
- D. ULPH, Rational conjectures in the theory of oligopoly, *International Journal of Industrial Organization*, 1, 1983, p. 131-154.
- G. UMBHAUER, *Forward induction and rationality of ϵ perturbations*, Working Paper BETA 9104 Université Louis-Pasteur Strasbourg, 1991 a.
- G. UMBHAUER, Information asymétrique et principes d'induction, *Revue Economique*, 42, 6, 1991 b, p. 1089-1110.
- E. VAN DAMME, Stability and perfection of Nash equilibria, Springer Verlag, 1987.
- E. VAN DAMME, *Refinements of Nash equilibrium*, 6th World Congress of The Econometric Society, Barcelona, 1990.
- P. H. YOUNG, The evolution of conventions, *Econometrica*, 61, 1, 1993, p. 57-84.

EVOLUTION STRATEGIES SIMPLE "MODELS" OF NATURAL PROCESSES?

Frank KURSAWE¹

Abstract

Optimisation algorithms imitating nature have proved their usefulness in various domains of applications. Annealing processes, central nervous systems and biological evolution in turn have lead to independent optimisation methods. The field of evolutionary computation comprises genetic algorithms, genetic programming, evolutionary programming and *evolution strategies* on which this paper will focus. Because these algorithms can also serve as simple models of the underlying natural processes, why not forget about the problem solving capabilities for a moment and put the emphasis on self-adapting behaviour? And why not translate these results to other domains, thus stressing the similarity of the notions 'self-organisation' and 'evolution' and their usefulness a common descriptive language across the scientific disciplines?

Résumé

Depuis quelques années, les algorithmes d'optimisation (globale) imitant certains principes de la nature, ont pu démontrer leur utilité dans des domaines d'application variés. *Annealing processes*, le système nerveux central et l'évolution biologique ont chacun conduit à des méthodes d'optimisation indépendantes. Le domaine de calcul évolutionniste comprend les algorithmes génétiques, la programmation génétique, la programmation évolutionniste et les stratégies évolutionnistes sur lesquelles cet article sera focalisé. Puisque ces algorithmes peuvent aussi servir de modèles simples pour les processus naturels qu'ils représentent, pourquoi n'oublions-nous pas leur capacité à résoudre des problèmes afin d'étudier leur comportement auto-adaptatif? Et pourquoi ne pas étendre ces résultats à d'autres domaines, soulignant ainsi la similitude de notions telles que « *self-organisation* » and « *evolution* » ainsi que leur utilité en tant que langage descriptif commun à plusieurs disciplines scientifiques?

1. Department of Computer Science, Chair of Systems Analysis, 44221 Dortmund, Germany.

I. INTRODUCTION

Suppose you have to solve the following problem: According to some quality criterion (objective function, model) you are looking for such a setting of the parameters (inputs, regulators in Figure 1) that the output reaches its (global) optimum.

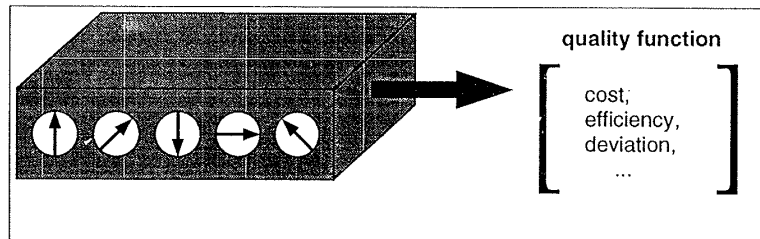


Figure 1. The 'black box'-model of optimization.

Mathematically speaking: Given a quality function (model)

$$f: M \subseteq \mathbb{R}^n \rightarrow \mathbb{R},$$

find a parameter setting $\vec{x}^* \in M$ so that

$$f(\vec{x}) \leq f(\vec{x}^*)$$

holds for all $\vec{x} \in M$. Often this abbreviates to $f(\vec{x}) \rightarrow \max. f(\vec{x}^*)$ is called *global maximum*. Because of $\max\{f(\vec{x})\} = -\min\{-f(\vec{x})\}$ the minimization task is equivalent.

What can you do in order to solve this problem?

1. You can try to either gain more or exploit your existing knowledge about the interior of the black box. If the objective function turns out to be smooth and differentiable (see *e.g.* Figure 2, left) analytical methods will produce the exact solution.

2. If this turns out to be impossible you might try the brute force method of enumerating the entire search space. But with the number of possibilities growing exponentially in n —the number of dimensions (inputs)—this method becomes infeasible already in low-dimensional spaces.

3. That is why mathematicians have tried to develop a theory for certain kinds of problems leading to specialized optimization procedures. These algorithms perform well if the black box fulfils their respective prerequisites.

For example, Dantzig's *simplex algorithm* (Dantzig, 1966) probably represents the best known multidimensional method capable of efficiently finding the global optimum of a linear, hence convex, objective function in a search space limited by linear constraints.

Gradient strategies are no longer tied to these linear worlds, but they 'smooth' their world by exploiting the objective function's first partial derivatives which have to be supplied in advance. Therefore, these algorithms rely on a locally linear internal model of the black box. *Newton strategies* additionally require the second partial derivatives, thus building a quadratic internal model. *Quasi-Newton*, *conjugate gradient* and *variable metric strategies* approximate this information during the search.

The deterministic strategies mentioned so far cannot cope with deteriorations, so the search will be stopped if anticipated improvements no longer occur. In a multimodal environment (see *e.g.* Figure 2, right), these algorithms move "uphill" from their respective starting points. Hence, they can only converge to the next local optimum. Newton-Raphson-methods might even diverge if there is a discrepancy between their internal assumptions and reality. But of course, these methods turn out to be superior if a given task matches their requirements. Not relying on derivatives, *polyeder strategy*, *pattern search* and *rotating coordinate search* should also be mentioned here because they represent robust non-linear optimization algorithms (Schwefel, 1981).

4. Dealing with technical optimization problems one will rarely be able to write down the objective function in a closed form $\vec{x} \rightarrow f(\vec{x})$. Often you need a *simulation model* in order to capture reality. In general, you cannot even expect these models to behave smoothly. Consequently, derivatives do not exist. That is why optimization algorithms have been developed which can successfully deal with black box-type situations. The increasing applicability is of course paid for by a loss of convergence velocity—compared to algorithms specially designed for the given problem. Furthermore, the guarantee to find the global optimum no longer exists.

But why turn to nature when looking for more powerful algorithms?

In the attempt to create tools for various purposes mankind has copied—often instinctively—solutions 'invented' by nature. Nowadays, it can be proven in some cases that certain forms or structures are not only well adapted to their environment but have even reached the optimum (Rosen, 1967). This is due to the fact that the laws of nature have remained stable during the last 3.5 billion years. For instance, at branching points the ratio of the diameters in a system of blood-vessels is close to the theoretical optimum

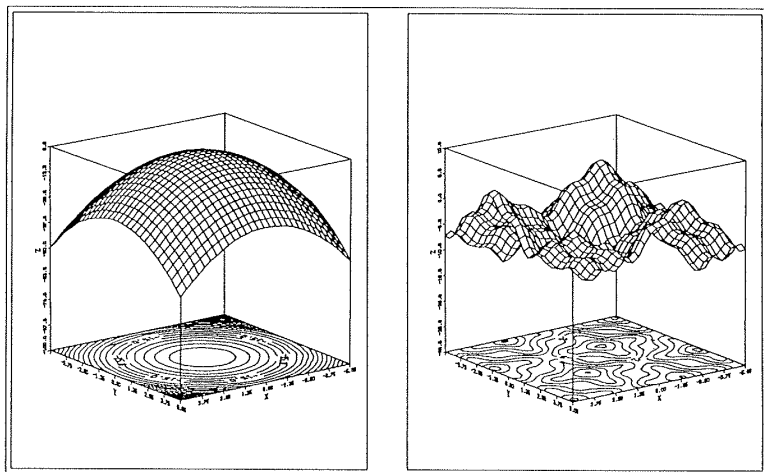


Figure 2. Easy and difficult topologies of objective functions.

provided by the laws of fluid dynamics ($2^{-1/3}$). This, of course, only represents a limited, engineering point of view on nature. In general, nature performs *adaptation*, not optimization.

The idea to imitate basic principles of natural processes for optimum seeking procedures already emerged more than three decades ago (Bremermann, 1962; Rechenberg, 1973; Holland, 1975; Schwefel, 1977). Although these algorithms have proved to be robust and direct optimization tools, only during the last five years people have started to pay more attention. This is due to the fact that many people still look at organic evolution as a huge game of dice, thus ignoring the fact that this 'model' of evolution cannot have worked: A human germ-cell comprises approximately 50.000 genes, each of which consisting of about 300 triplets of nucleic bases. Although the four existing bases only encode 20 different amino acids, $20^{15.000.000} \approx 10^{19.500.000}$ different genotypes had to be tested in only $\approx 10^{17}$ seconds—the age of our planet. So, simply "rolling the dice" could indeed not have produced the diversity of complex living systems observable today. Accordingly, taking random samples from the high-dimensional parameter space of an objective function in order to hit the global optimum *must* fail (*Monte-Carlo search*). But by looking at organic evolution as a cumulative, highly parallel sieving process, the results of which pass on slightly modified into the next sieve, the amazing diversity and efficiency on earth no longer appears miraculous. When building a model, the point is to isolate the main mechanisms which have

led to today's world and which have been subjected to evolution themselves: Inevitably, nature has come up with a mechanism allowing individuals of one species to exchange parts of their genetic information (recombination or crossing-over), thus being able to meet changing environmental conditions in a better way.

Today, one may distinguish four types of *evolutionary algorithms*. For an introduction and a comparison of the first three, see (Bäck and Schwefel, 1993).

- *evolution strategies*
- evolutionary programming
- genetic algorithms
- genetic programming

In the following, this paper will focus on multimembered *evolution strategies* as proposed in (Schwefel, 1977 and 1981).

II. THE (μ^+, λ) EVOLUTION STRATEGY

Rechenberg (1973) and Schwefel (1977) developed the *evolution strategies* when they wanted to optimize technical objects like *e.g.* a flashing nozzle. No closed form analytical objective function was available, and hence, no applicable optimization method existed at that time. Their first attempt to imitate principles of organic evolution on a computer still resembled those iterative optimization methods known up to that time: In a two-membered or $(1+1)$ evolution strategy, one "parent" generates one offspring per generation by applying normally distributed mutations, i.e. smaller steps are more likely than big jumps, until a 'child' performs better than its ancestor and takes its place. Because of this simple structure, theoretical results for stepsize control and convergence velocity could be derived: The ratio between successful and all mutations should come to $1/5$. This first algorithm was then enhanced to a $(\mu + 1)$ strategy which incorporated recombination for the first time with several parents being available. The mutation scheme and the exogenous stepsize control were taken across unchanged.

Schwefel (1977, 1981) generalized these strategies to become the multimembered or (μ^+, λ) evolution strategy which imitates the following basic principles of organic evolution:

- population, leading to the possibility of
- recombination with random mating,

- mutation and
- selection

An 'individual' on the computer consists of the following 'genes' representing a point in the search space:

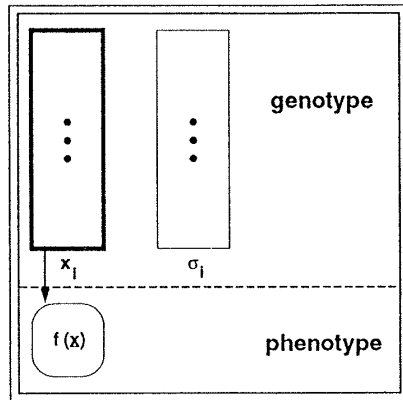


Figure 3. Structure of an individual.

- Real-valued *object variables* x_i have to be tuned by recombination and mutation in such a way that an objective function reaches its global optimum. Referring to the metaphor mentioned previously, the x_i represent the regulators of the black box in Figure 1.

- Real-valued *strategy variables* or mean 'stepsizes' σ_i determine the mutability of the x_i . They represent the standard deviation of a $(0, \sigma_i)$ Gaussian distribution being added to each x_i as an undirected mutation. With an expectancy value of 0, the parents will produce offsprings similar to themselves on average. In order to make a doubling and a halving of a stepsize equally probable, the σ_i mutate log-normally distributed from generation to generation. These stepsizes hide the internal 'model' the population has made of its environment so far. In other words, a self-adaptation of the stepsizes has taken over from the exogenous control of the $(1 + 1)$ strategy. This concept works because selection sooner or later prefers those individuals having built a good model of the objective function, thus producing better offsprings. Hence, learning takes place on two levels (see Figure 4).

- Depending on an individual's x_i , the resulting objective function value $f(\vec{x})$ serves as the 'phenotype' (fitness) in the selection step. In a plus

strategy, the μ best of all $(\mu + \lambda)$ individuals survive to become the parents of the next generation. Using the comma variant, selection takes place only among the λ offsprings. The second scheme is more realistic and therefore more successful, because no individual may survive forever—which could at least theoretically occur using the plus variant. Untypical for conventional optimization algorithms and lavish at first sight, a comma strategy allowing intermediate deterioration performs better: Only by 'forgetting' individuals with a good phenotype, which may have been achieved with an internal model that is no longer appropriate for further progress, a permanent adaptation of the stepsizes can take place and avoid long stagnation phases due to misadapted stepsizes.

By choosing a certain ratio μ/λ , one can determine the convergence property of the evolution strategy: If one wants a fast, but local convergence, one should choose a small ratio (e.g. (5, 100)), but looking for the global optimum, one should favour a 'softer' selection (e.g. (15, 100)). Figure 4 displays the self-adapting capabilities of different evolution strategies under varying selection pressure. Using

$$f(\vec{x}) := \sum_{i=1}^{30} (i \cdot x_i^2)$$

as the objective function, $n=30$ stepsizes have to be tuned properly with respect to each other in order to achieve maximum progress in adjusting the $n=30x_i$ on the first level.

Curve A represents the performance of a strategy provided with perfect 'knowledge' about its environment ($\sigma_i = c/\sqrt{i}$), whereas in B, randomly chosen relations of the σ_i were fixed. In curve C, the stepsizes could self-adapt by means of mutation and recombination. Not surprisingly, $\mu = 1$ proved to be the best choice for A and B where only one stepsize had to adapt, because all relations had been fixed. On the other hand, one should choose μ between 12 and 17 if one wants learning to take place (C). Two observations from Figure 4 are remarkable: The (15, 100) strategy converges nearly as fast as variant A, and it performs better than the (15, 100) strategy with perfect knowledge. One can regard this phenomenon as a *synergetic* effect: 15 'fools' perform better *collectively* than the same number of 'specialists'.

Self-adaptation within evolution strategies depends on the following 'agents' (Schwefel, 1987):

- One cannot model mutation as a 'pure' random process. This would mean that a child is completely independent of its parents.

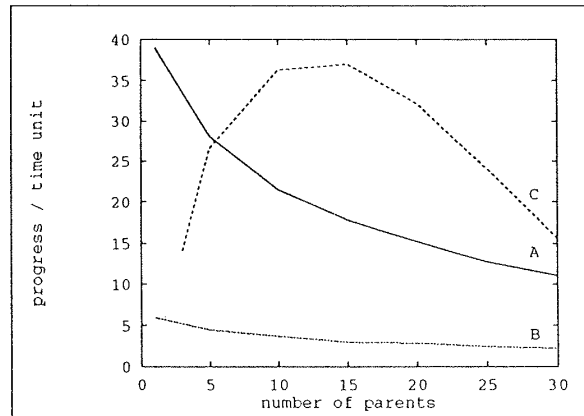


Figure 4. Optimum selection pressure.

- The population has to be sufficiently large. Not only the 'current best' should be allowed to reproduce, but a set of good individuals. Biologists have coined the term 'requisite variety' being necessary to prevent a species from becoming poorer and poorer genetically, eventually dying out.

- In order to exploit the effects of a population ($\mu > 1$), the individuals should recombine their knowledge with that of others (cooperate) because one cannot expect the knowledge to accumulate in the best individual only.

- In order to allow better internal models (stepsizes) to provide better progress in the future, one should accept deterioration from one generation to the next. A limited life-span in nature is not a sign of failure, but an important means of preventing a species from 'freezing' genetically.

Evolution strategies have proven their capacity on a large number of test problems in an extensive comparison with other iterative methods (Schwefel, 1977). They are adaptable to nearly all sorts of problems in optimization, because they need very little information about the problem—especially no derivatives of the objective function. For a list of more than 260 applications of evolutionary algorithms, see (Bäck *et al.*, 1992). They are capable of solving high dimensional, multimodal, nonlinear problems subject to linear and/or nonlinear constraints. The objective function can also hide the result of a simulation, it does not have to be given in a closed form. This also holds for the constraints which may represent the outcome of a finite elements method (FEM). Evolution strategies have been adapted to vector optimization problems (Kursawe, 1992), and they can also solve NP-complete problems

like the *travelling salesman problem* or problems with a noisy or changing response surface.

But apart from focusing on their problem solving capacity, one may also concentrate on the conditions under which self-adaptation takes place in evolution strategies. And why not transfer these results—although originating from an ideal and artificial world—to other, real-life domains?

III. TRANSFERRING THE OBSERVATIONS TO...

3.1. ...Biology

Since evolution strategies rely upon the collective learning paradigm of natural populations introduced by Darwin and embedded in today's synthetic theory of evolution, using these strategies as a model of biological processes seems obvious.

- As stated before, a limited life-span enables a species to cope with an environment undergoing change. Accordingly, only a comma strategy allowing each parental generation to reproduce exactly once is able to follow an optimum wandering over time. Holding on to good, but outdated phenotypes the plus variant fails to perform this task.

- So far, evolution strategies only use haploid individuals, thus abandoning the effects of dominance and recessivity. Diploid individuals are not worth the additional computing time in an environment remaining stable over time, *i.e.* in the case of one objective function. But when evolution strategies try to compute the Pareto set of a vector optimization task, the selection step has to be modified in such a way that each of the $k (> 1)$ objective functions becomes the selection criterion according to a probability vector. From an individual's point of view, the environment changes rather drastically which is why diploid individuals turn out to be necessary in the multiple criteria case. And again, one can find a biological analogy: For certain plants the relation

$$\text{degree of polyploidy in percent} = \text{latitude}$$

holds. Measuring time on a geological scale, in Greenland, the past-glacial environment may be regarded as relatively young compared to the environment in south of Greece which has not changed during the last ice-age.

- The basic mechanisms of organic evolution have undergone an evolution themselves, too: Nature has 'invented' (sexual) recombination as a means

of exchanging genetic material between the individuals of one species in order to prevent parasites from adapting to a certain genotype too well. In a difficult topology like the one in Figure 2 on the right, recombination also turns out to be crucial for finding the global optimum and not just a local one (convergence security):

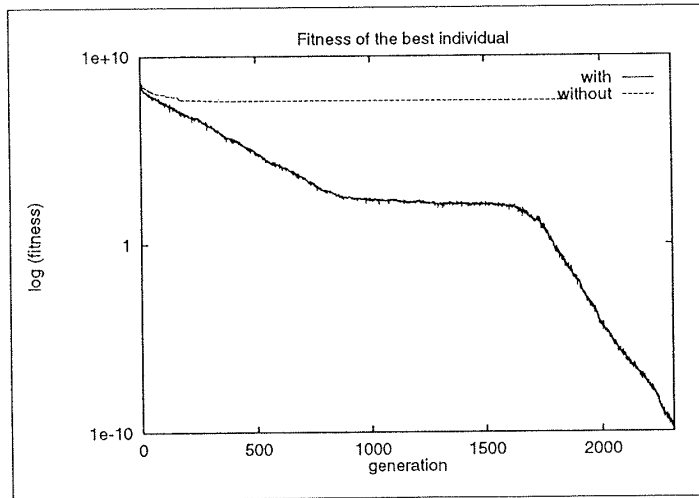


Figure 5. A (15, 100) strategy with and without recombination.

• Schwefel (1975) developed a variant of evolution strategies being capable of solving discrete (here: binary) problems by modelling somatic mutations. The observation of an ambiguous relation between an individual's genotype and phenotype forms the biological background of this idea. This 'disturbed' relation can be interpreted and modelled as the result of errors happening during ontogenesis. If this hypothesis of a connection between the genetic mutation rate and the somatic error rate is correct this model may help to explain the non-genetic variance of morphological attributes (*e.g.* body length, tail length, weight, ...) observable within populations of genetically identical mammals.

Again, within the algorithm, learning takes place on two levels: On the first level, 100 bits have to set correctly. This is achieved by attaching to each bit its private mutation probability. For those bits which have already been set correctly this rate remains near its starting value ($\approx 10^{-6}$), whereas the

wrong bits have to increase their mutability to such a value ($\approx 10^{-2}$) that the desired mutation finally occurs. Afterwards, this value has to decrease again in order to prevent the correct bit from flipping once more. In contrast to the previous one, Figure 6 now demonstrates the influence of recombination on convergence velocity:

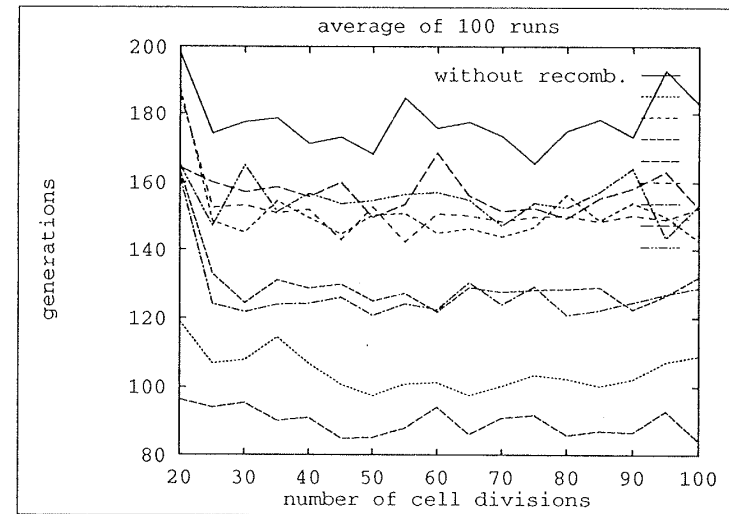


Figure 6. A modified (15, 100) strategy using different types of recombination.

Setting all mutation probabilities to 10^{-6} , one can expect to perform $\approx 1.800.000$ trials until the last three bits have been set correctly preserving the correct bits. The modified evolution strategy only needs ≈ 9.000 mutations using recombination, thus emphasizing again that nature cannot be regarded as a pure random walk.

3.2. ...Organizational Psychology

Darwin's basic assumption that organisms can only survive if they perform some sort of adaptation within their environment has inspired psychologists being occupied with the organizational structure of firms: Why should *one* organizational structure exist which performs equally well in all sorts of

situations? On the contrary, different environments ask for different, specially adapted structures. This rather situational or contingency approach has empirically found out that bureaucratic organizations most easily prosper in stationary or settled surroundings. But dynamical environments demand for the internal adaptability of so-called organic organizations relying on well-educated and autonomous, self-supporting members. In this context, knowledge can be regarded as a social product enabled by and permanently expanded and corrected by an exchange of ideas. If practical problems go beyond the limits of one scientific discipline one does not necessarily need inventions. Often the required knowledge already exists, but the respective 'owners' fail to discover its relevance within the given problem's frame of reference.

In evolution strategies, the recombination operator 'exchanges ideas' – the existing knowledge hidden in the stepsizes. As stated before, abandoning recombination (cooperation) when solving a simple problem only leads to a loss of efficiency (see Figure 6), but facing a difficult task the solution yielded will be far from the global optimum (see Figure 5).

There are hints that, under certain, but rare conditions, the formation of a group adapts to the task's complexity: In the case of simple problems, centralized network structures develop, whereas complex tasks lead to decentralized structures. Within existing organizations, formal hierarchies normally prevent this process.

The design of a meta-evolution strategy capable of adapting population size, selection pressure and recombination type is currently under development. This algorithm should confirm the following result: In a smooth and simple world like the one in Figure 2 (left), a (1, 100) strategy with only one stepsize for all x_i performs far better than a (15, 100) strategy with 30 stepsizes which in turn is more appropriate in difficult, multimodal environments:

The notions 'lean management' and 'lean production' may also fit into the frame of this section. They have originated from a 1990 MIT study which tried to convey a Japanese concept – known as the *Toyota production system* since 1973 already – to the U.S. car industry. Often, 'lean' is being misunderstood nowadays as a justification of dismissals. Doing so can reduce the unspecific – in an economic sense: unnecessary – resources or the requisite variety in such a way that a change in the outside world becomes more difficult to cope with. But with the true background being the idea of a *lean organization* one should concentrate on integrating those activities not being involved directly in the production process, like *e.g.* surveillance, quality control and maintenance. Shifting these functions to the worker the

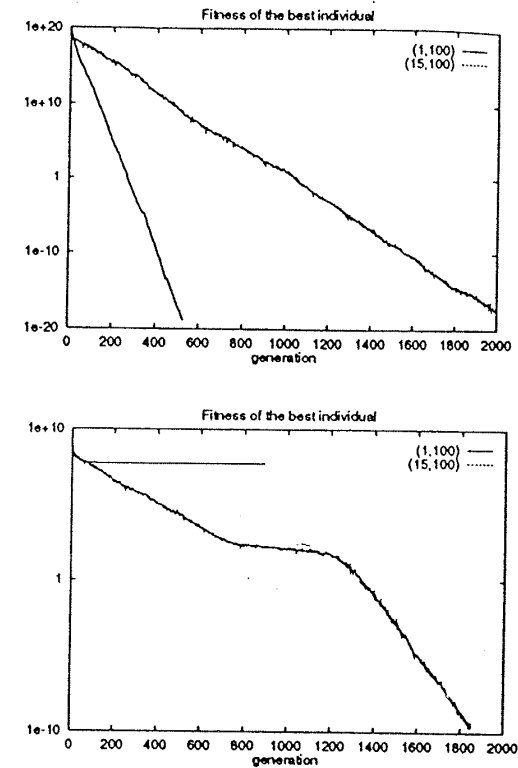


Figure 7. A (1, 100) versus a (15, 100) strategy competing in the topologies of Figure 2, $n = 30$.

enhanced responsibility leads to a more interesting job, thus establishing a feedback loop between a worker's creative abilities and his/her own working conditions. Additionally, regular discussions ('quality circles') held across several hierarchical layers promote the distribution of knowledge.

3.3. ...Economics

The main principle of synergetics consists in explaining an observable order from within the system or *endogenously*. In economics, the *invisible hand* (Adam Smith) already conveyed the idea of self-organizing markets in order to explain how individual decisions lead to the formation of structures. With this idea serving as a descriptive 'theory' only, the scientific

interest shifted towards the analysis of market equilibria using the laws of mechanics. Nowadays, *evolutionary economics* no longer examine the process of converging against an equilibrium but rather concentrate on the formation and diffusion of innovations. Furthermore, time has become irreversible: The history of an economic process has to be considered when explaining its further development.

With concepts like the 'bounded rationality' trying to overcome the idealistic assumption of an agent's intentional behaviour, why not model individuals stochastically in order to capture the variety of behavioural norms? With a selection step present (externalities) a long-term macroscopic order may emerge which in turn effects or even 'enslaves' the 'fast' variables on the lower level. A market can remain stable for a certain time, but when approaching one of this stable 'island's' borders, already small variations can lead to a new state of order (bifurcation or path-dependencies, lock-in effects). The victory of the VHS video system over the Beta video system, which was said to be superior technically, depended on a small majority of people preferring VHS in the beginning (Briggs and Peat, 1989). Externalities have a strong influence in this example: The more widespread one system is, the better the support from the complementary good markets. Consequently, the decision depends on the perception of the number of systems already sold and the expected utility assigned to it.

Figure 8 displays the performance of an evolution strategy under high selective pressure. There are phases of stagnation and phases of rapid change emerging endogenously—a phenomenon biologists refer to as 'punctuated equilibria' (Eldredge and Gould, 1972, 1977).

Maybe, unwanted discontinuities can be overcome by a closer 'cooperation' between economies, too. And maybe, a sustainable growth can only be achieved in this way—if it exists at all. The last worldwide stock market crash (without any serious economic foundation) has demonstrated how sensitively markets with selfish, maximizing agents, rigid rules and a deceptive security respond to small disturbances. But if the assumption of continuity is wrong (Boulding, 1991), maybe recessive phases help to 'forget' traditional technologies, firms and institutions releasing niches for the entry of innovative elements, thus enhancing diversity and resulting in a more robust economy (Eliasson, 1991).

The assumption of a nonlinear world surrounding us bears consequences: For we do *not* know exactly what we are doing when interfering with any kind of system comprising nonlinearities. Even the best intentions can lead to unbounded consequences.

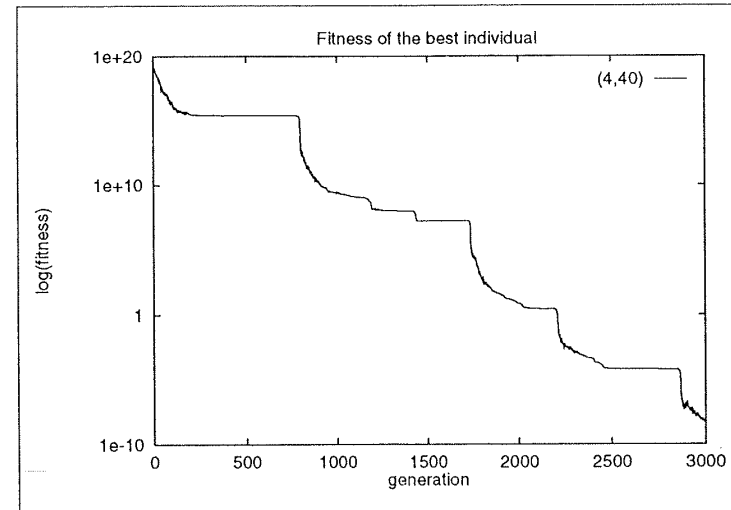


Figure 8. A (4, 40) strategy adjusting 30 parameters.

References

- T. BÄCK, F. HOFFMEISTER, H.-P. SCHWEFEL, *Applications of evolutionary algorithms*, Report of the Systems Analysis Research Group SYS-2/92, University of Dortmund, Department of Computer Science, 1992.
- T. BÄCK, H.-P. SCHWEFEL, An overview of evolutionary algorithms for parameter optimization, *Evolutionary Computation*, 1993, 1, p. 1-23.
- K. E. BOULDING, What is evolutionary economics?, *Journal of Evolutionary Economics*, 1991, 1, p. 9-17.
- H. J. BREMERMAN, Optimization through evolution and recombination, in: *Self-Organizing Systems*, M. C. Yovits, G. T. Jacobi and D. G. Goldstein (Eds.), Spartan Books, Washington, D.C., 1962, p. 93-106.
- J. BRIGGS, F. D. PEAT, *Turbulent Mirror—An Illustrated Guide to Chaos Theory and the Science of Wholeness*, Harper & Row Publishers, New York, 1989.
- G. B. DANTZIG, *Lineare Programmierung und Erweiterungen*, Springer, Berlin, 1966.
- N. ELDRIDGE, S. J. GOULD, Punctuated equilibria: An alternative to phyletic gradualism, in: *Models in Paleobiology*, T. J. M. Schopf (Ed.), Freeman, 1972, Chapter 5, p. 82-115.
- N. ELDRIDGE, S. J. GOULD, Punctuated equilibria: The tempo and mode of evolution reconsidered, *Paleobiology*, 1977, 3, p. 115-151.
- G. ELIASSON, Deregulation, innovative entry and structural diversity, *Journal of Evolutionary Economics*, 1991, 1, p. 49-63.
- J. H. HOLLAND, *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor, Michigan, 1975.

F. KURSAWE, *Evolution strategies for vector optimization*, Taipei, 1992, National Chiao Tung University, p. 187-193.

I. RECHENBERG, *Evolutionsstrategie: Optimierung technischer Systeme nach Prinzipien der biologischen Evolution*, Frommann-Holzboog, Stuttgart, 1973.

R. ROSEN, *Optimality Principles in Biology*, Butterworths, London, 1967.

H.-P. SCHWEFEL, *Binäre Optimierung durch somatische Mutation*, tech. rep., Technical University of Berlin and Medical University of Hannover, May 1975.

H.-P. SCHWEFEL, *Numerische Optimierung von Computer-Modellen mittels der Evolutionsstrategie*, Birkhäuser, Basel, 1977.

H.-P. SCHWEFEL, *Numerical Optimization of Computer Models*, Wiley & Sons, Chichester, 1981.

H.-P. SCHWEFEL, *Collective phenomena in evolutionary systems*, in: 31st Annual Meeting of the International Society for General System Research, Budapest, 1987, p. 1025-1033.

Adhérez à l' **afcet**

pour comprendre, utiliser, promouvoir les sciences et technologies de l'information et des systèmes et participer à leur formidable évolution.

Association, sans but lucratif (loi 1901), reconnue d'utilité publique, l'AF CET constitue un lieu de rencontre unique et irremplaçable pour ses **2500 membres** provenant d'horizons divers: **recherche, enseignement, industrie, commerce, services, du secteur privé comme du secteur public.**

Par l'édition de 8 revues spécialisées ainsi que par l'organisation annuelle d'une vingtaine de manifestations locales, nationales ou internationales, **l'AF CET assure un rôle de diffusion de connaissances.** Elle affirme ainsi sa présence dans le monde de la communication scientifique et technique, nationale autant qu'internationale.

Ses 13 Comités techniques coordonnent les activités des groupes de travail et impulsent des activités concertées liées à leurs domaines : (séances de réflexion, rapports d'orientation, publications, journées d'étude, congrès)

Comités Techniques :

- | | |
|--|--|
| • Aide à la décision et recherche opérationnelle | • Informatique fondamentale |
| • Architecture des systèmes informatiques | • Intelligence artificielle et reconnaissance des formes |
| • Automatique et productique | • Langages de programmation et génie logiciel |
| • Bases de données | • Sécurité et sûreté informatiques |
| • Bureautique : document, groupware, multimedia | • Systèmes d'information |
| • Cultures, techniques et organisation | • Systémique et cognition |
| | • Vie artificielle |

Groupes de Travail :

Les groupes de travail (plus de 90) constituent un lieu privilégié de rencontres régulières des membres de l'Association venant de tous les horizons, favorisant la confrontation de leurs expériences et de leurs besoins.

Relations Internationales :

Par sa participation à de nombreuses fédérations internationales l'AF CET contribue à diffuser les travaux français dans le monde entier.

*Demande de renseignements : AF CET, 156 Bd Péreire - 75017 Paris - Tél. : 47 66 24 19
Fax : 42 67 93 12*

Nom : Prénom:.....
Organisme :
Adresse:.....

Code postal : Ville : Fax

- Désire recevoir des informations : sur les revues les groupes de travail
les fédérations internationales les congrès
• Désire recevoir une feuille d'adhésion 1994