Satisfcing, Deliberate Experimentation and Designing Without Final Goals: Modeling Innovation-Related Business Strategy Choice through Simulation Analysis

Second Draft

Karén Hovhannisian

ISER, University of Siena
MERIT, University of Maastricht

Email : khovha@hotmail.com
k.hovhannisian@merit.unimaas.nl

December, 2002

Introduction[1]

In the recent years, a number of economists and organizational scientist have started to work on a new approach to analyze the dynamics of innovation driven technological and institutional change. The standard search models heavily relying on the neoclassical assumptions and apparatus are seen now as incomplete, in what they neglect the interconnectedness between the elements of any complex system, leading to results neither intuitive, nor corresponding to the real business life data.

This new approach is based upon the nowadays-fast evolving research in the fields of evolutionary biology and evolutionary programming that in their own turn are built upon the apparatus of the physical spin-glass models and the binary networks idea.

What the new approach seen from the point of view of the economics proper suggests, is to view the firms and the technologies they use as production recipes rather than production functions. The difference between the two is that while the latter presupposes a system defined solely by the elements it is comprised of and their quantity (or quality), the former approach, above all that, puts the emphasis on the question of in what way are the elements comprising a system combined with each other, implying that the links between the elements are as important factors in characterizing the behavior of the system as a whole as the elements themselves.

The word recipe itself leads to a very intuitive example explaining the importance of that proposition. It is indeed not enough to know just the list of the ingredients (elements) such as flour, water, salt, yeast and the temperature of the oven, together with their relative quantities to bake a loaf of bread, but we also need to know how those ingredients are combined, in what sequence they have to be used and so on. This is just as true when we talk about, say, producing a car rather than baking a loaf of bread, or, indeed, when we talk about designing the whole organizational and technological structure of a firm.

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[1] The author would like to thank Koen Frenken, Marco Valente, Esben S. Andersen, Ugo Pagano, Patrick Llerena, Brian Loasby and the participants of the DRUID 2002 Winter Conference, University of Siena Seminar Series and ETIC-LAB Workshop for their comments and suggestions on the previous draft of the paper. All the mistakes and omissions are however mine only.

However exiting and novel are the results and the implications obtained from applying the abovementioned methodology to the question of firm-level innovation dynamics, I propose in this paper that we have to be extremely careful when trying to explain the evolution of the economic or for that matter any social system using the insights and the techniques borrowed from the natural or artificial systems studies.

Ever since Sewell Wright's seminal paper (Wright (1932)), the allusion to *fitness landscapes* is being made, first in the field of biology, and now, increasingly spreading to the studies of various complex systems' evolution, including the economic systems. The agents (be they biological species, individuals, firms or economies as a whole) are seen to be searching on multidimensional fitness (technological, organizational) landscapes for the *peaks* that for example can be seen in economic applications as the configurations corresponding to the profit levels higher than that of any neighboring configurations.

We can indeed see the purely taken neoclassical microeconomic theory as a subcase of the *landscape theory*, where there exist only one peak on the terrain, which assuming the agents to be rational, is accessible by all of them, leading to a homogenous population of agents each functioning at a zero profit level.

Much more interesting and complex dynamics can be observed however for the cases where the terrain is multipeaked (and thus there exist multiple equilibria), with the peaks not at all necessarily of the same height (and thus with some of the equilibria being suboptimal). In this case, assuming that firms are incapable of making a radical innovation, or, alternatively, that they rationally choose not to innovate radically, realizing that the probability of it being a complete flop is much higher than the probability of success, there is nothing in the structure of the problem guaranteeing the formation of a homogenous population of firms.

Indeed, if the peaks (both global and local) are characterized by their being superior to any neighboring configuration, the latter are the only ones accessible in any single period by a firm, and the firm is assumed to be rational in what it would not accept a shift to a configuration inferior to the one currently employed, then any peak, however low it can be compared to the global optimum, is a perfect mousetrap, from where there is no way out ever[2].

In fact, the early models of search on the technological landscapes (cf. Kauffman, Macready & Dickinson (1994), Kauffman & Macredy (1995), Kauffman, Lobo & Macready (2000), Levinthal (1997, 2000), Lobo & Macready (1999)) based upon the original NK framework designed in the field of evolutionary biology by Kauffman and his colleagues (Kauffman & Levin (1987), Kauffman (1989ab, 1993)) were pretty pessimistic, because while radical innovations in vast majority of the cases were seen to be leading to a significant fall in the performance of a firm (especially of a firm with at least moderately good initial performance), incremental innovations were leading the firms to suboptimal peaks from where they had no chance to escape. The evolution would then stop once all the firms under consideration would reach such a peak.

Such a picture was not very realistic and in fact both within and outside the field of economics, various attempts to augment the model to account for a more plausible scenario were made. Very interesting lines of research was initiated to include in the analysis factors such as *neutrality* (Huynen, Stadler & Fontana (1995), Huynen (1996), Barnett (1997, 1998), Ancel & Fontana (1999)), *exogenous shifts in the landscapes* (Kauffman (1993, 1995), McKelvey (1997)), *constructional selection mediated growth* (Altenberg (1994, 1997), Wagner (1995)), and such, proposing various ways in which firms can avoid the traps and evolve towards a better performance level in complex environments.[3]

The current paper builds upon another line of research in this field that puts the emphasis on *modularity and decomposability* (Frenken, Marengo & Valente (1999), Marengo *et al*. (2000, 2001), Frenken (2002)). Probably the main attraction of those papers is in the fact that optimizing behavior of the agents is substituted for *satisficing*.

Following Herbert Simon's logic (see Simon (1955), (1969)), they claim that an optimal solution does not have to be an end achieved by all means. In problems of even a very moderate complexity, finding an optimal solution is too costly if at all possible. On

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[2] Of course, in this formulation, perfect rationality is *myopic* as e.g. in Rosenberg's *Centipede Game*.

[3] See also Hovhannisian (2002b) for an overview of these models and the reinterpretation in economic terminology of those among them taken from other fields.

the other hand, it is possible to find a "good enough" solution with much lesser effort. The comparison of the agents with different search strategies shows indeed that the ones who satisfice quite often outcompete the pure optimizers.

This line of research, however, suggests that satisficing applies only to the end-results of the process, while the search for those "good-enough" solutions within the set of now available ones, still proceeds in a purely optimizing manner. If so, then the authors implicitly suggest the existence of some final goals in design activities.

However, in the same book by Simon from where Frenken and his colleagues borrow the notions of *satisficing behavior* and *decomposable systems*, one can find an argument against considering such final goals.[4]

Simon writes: "A paradoxical, but perhaps realistic, view of design goals is that their function is to motivate activity which in turn will generate new goals".[5] And again, "Exposure to new experiences is almost certain to change the criteria of choice, and most human beings deliberately seek out such experience".[6]

Organizational and technological design is indeed an open-end process, and if so, there seems to be no reason, or even a possibility, to view some steps in this process as leading to "more final" goals than others. Therefore it seems to be quite natural in the world of designing without final goals, to augment the idea of accepting "good-enough" end results with a mechanism of taking "good-enough" decisions in each step of organizational and technological design process.

Defining a Research Framework

1.1. Kauffman's NK Model

Kauffman (1993) developed the 'NK fitness landscape' model to provide a formal and abstract measure of the statistical structure of the rugged fitness landscapes. Despite

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[4] **Simon, Herbert (1969 [1996])** *The Sciences of the Artificial.* The MIT Press, Cambridge, MA. *pages 162-163*

[5] **ibid.**, *page 162*

[6] **ibid.**, *page 162*

the fact that the model was developed in the field of *evolutionary biology*, and primarily devised to study the mutations of *genes* in an organism, the origins of it are not biological. The NK model is based on spin-glass models from physics, enriched by the insights from the binary network dynamics models from the computer science, in order to account for the interactions of the system with the environment.

The main elements of the model are the *N* and *K* parameters, where the former stands for the number of parts in the system, while the latter measures how cross-coupled the system is, or, how interrelated the elements comprising the system are.

The lower is *K* (with the limit case of *K=0*) the lesser is the probability of affecting the other *N-1* elements of the system when changing some element *i* of it, and hence, the easier it is to reach a global optimum through *one-bit mutations*. The *landscapes* on which the process of search takes place, are then said to be *smooth*, of the form close to that of *Gaussian* distribution.

The higher is *K* (with the limit case of *K=N-1*) the higher that probability gets, changing the structure of the landscapes from smooth into *rugged* and then *jagged*. The *rugged landscapes* are characterized by multiplicity of local optima of differing fitness level, each with a proper *basin of attraction* of various sizes[7]. The higher *K* gets then, the higher is the probability of the system being trapped on sub-optimal local optima, where the latter is characterized by the condition that no one-bit mutations lead to an improvement in fitness level. The allusion that can help better visualize that case it of a mountainous terrain, with mountain peaks of different height, and wide valleys and narrow gorges between them.

With *K* approaching the maximum value of *N-1*, the landscape becomes completely uncorrelated. A change in any of the elements in the system brings about

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[7] While formally a notion of a basin of attraction refers to minima to which all the configurations from some neighborhood come down to, here we turn the term upside down, to talk of the optima with a maximal fitness compared to the level of fitness of the neighboring configurations.

changes in each and all the rest of the elements of that system, and a *house of cards* effect prevails.[8]

The landscapes are then said to be *random* which means that the current position of the system on a landscape does not infer any information whatsoever about the neighboring positions.

Another parameter of the model is A, which is in biological terminology a number of *alleles* in which a gene can occur. Broader speaking, A is the number of states in which each element can find itself. While A can accept any positive value, for the simplicity, and for being able to utilize the model of binary strings, it's value is usually kept for each element to be equal to 2.

Consequently, the fitness contribution w_j of each gene (element) is drawn randomly from the A^{K+1} (or in case of $A=2$, from 2^{K+1}) possible allele (state) combinations of the element itself and the K other elements, whose state affects the fitness contribution of the given element.

The fitness of the whole system θ then is given by the mean of the fitness values of its elements:

$$\theta = \frac{1}{N}\sum_{i=1}^{N}\theta_i(x_i;x_{i1};\ldots;x_{iK}) \qquad (1)$$

where $\{i_1,\ldots,i_K\} \subset \{1,\ldots,i-1,i+1,\ldots,N\}$.

Some results from the simulation runs of the model with various values of K are summarized below[9].

For K=0:

- There is a single global optimum, and any genotypes below it are guaranteed to reach it in finite time
- The expected number of steps to the global optimum are *N/2*

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[8] The *house of cards* effect is an allusion to pulling a card from a house of cards, which apparently makes the whole house tumble down, without transferring any information from its previous value (the position of different cards) when we want to rebuild it.

[9] These results are adapted from Kauffman (1993), as well as Weinberger (1996) and Altenberg (1997)

- Walk lengths increase linearly in N

For K=N-1:

- Number of local optima is extremely large for large N, $2^N/(N+1)$
- At each step, the expected number of fitter neighbors decreases by ½
- The expected time of reaching an optimum is: $\sum_{i=0}^{\log_2(N-1)-1} 2^i$
- As complexity increases, the height of accessible peaks falls toward the mean fitness[10]

For 0<K<N-1:

- As K increases the correlation of the landscape decreases, so that if for small values of K the peaks are located nearby, with an increase in K their distribution becomes increasingly random, with the average distance between the two determined by: $\frac{N \log_2(K+1)}{2(K+1)}$
- For sufficiently large K, the mean fitness of local optima is: $\mu + \sigma\sqrt{\frac{2\ln(K+1)}{K+1}}$, with a variance of: $\frac{(K+1)\sigma^2}{N[K+1+2(K+2)\ln(K+1)]}$, where μ is the expected value of θ_i, σ^2 its variance.

1.2. Search on Technology Landscapes

Using the *NK* framework, Lobo & Macready (1999), and Kauffman *et al.* (2000) have developed a model of search on technology landscapes. Here, the familiar notion of a firm's production plan as a point in an input-output space is replaced with a broader concept of a *production recipe*[11].

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[10] This is what Kauffman calls "a complexity catastrophe": Kauffman (1993), *page 52.*

[11] This concept is developed at large by Auerswald & Lobo (1996), and Auerswald *et al.* (2000)

A production recipe is said to consist of N distinct operations, each of which occupying one of S distinct states. A measure of production “intranalities”, e, is introduced, that plays the same role as K in NK framework. Formally, the ith recipe w_i is represented by:

$$w_i = \left\{ w_i^1, \ldots, w_i^j, \ldots, w_i^N \right\} \tag{2}$$

where $w_i^j \in \left\{ 1, \ldots, S \right\}$ is the description of the jth operation for $j = 1, \ldots, N$.

Subsequently, we can compute the *fitness level* or the efficiency of a given production recipe through the following formula:

$$\theta(w_i) = \frac{1}{N} \sum_{j=1}^{N} \phi_i^j = \frac{1}{N} \sum_{j=1}^{N} \phi^j \left(w_i^j ; w_i^{j_i}, \ldots, w_i^{j_e} \right) \tag{3}$$

with $\varphi_i^j = \varphi^j (w_i^j, w_i^{-j})$ defined as the efficiency of the jth operation, and j_i, $i=1 \ldots e$, being the set of operations affecting the jth operation.

Lobo and Macready (1999) provide the following definition: “A *technology landscape* consists of (1) a profit function assigning a real-valued number to each technology in the space of possible technological configurations; and (2) a metric structure over the space of technological possibilities which reflects whether any two given technologies are “close” to one another or “distant” from each other.”[12]

So, what we need to know is how good each technological configuration is, and where is it placed on the landscape compared to the other possible configurations.

In economic terminology, we can then restate that the total profitability of the technological configuration is defined as the average of the profitabilities of each operation it is comprised with:

$$r(w_i) = \frac{1}{N} \sum_{j=1}^{N} r^j(w_i) \tag{4}$$

Each configuration in its own turn consists of a number of elements, or as Lobo & Macready call them, *operations*, with an assigned *states* to each of those. Then, in order to see how far or close on the technology landscape is the technological configuration to which a firm wants to shift from the one currently employed, we need to check how different are the elements of those two configurations, or how many elements need to be

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[12] **Lobo, José & William G. Macready (1999)** *Landscapes: A Natural Extension of Search Theory*, Santa Fe Institute Working Paper 99-05-037 E, *page1*

changed in order to make that passage. As Kauffman *et al*. (2000) write: “More precisely, the *distance* $d(\omega_i, \omega_j)$ between the production recipes ω_i and ω_j is the *minimum* number of operations which must be changed in order to convert ω_i to ω_j.”[13] Here, “The firm’s production recipe encompasses all of the deliberate organizational and technical practices which, when performed together, result in a production of a specific good.”[14]

The set of *neighbors* for a given production recipe then is defined by:

$$H_d(w_i) = \{w_j \in \{\Omega - w_i\} : d(w_i, w_j) = d\} \ , \qquad (5)$$

where $H_d(w_i)$ is the set of *d-neighbors* of w_i, with $d \in \{0,..,N\}$, and Ω is the set of all possible production recipes, with: $\theta : w_i \in \Omega \rightarrow \Re^{++}$.

The firm performs the search on the landscape through a random walk. Kauffman et. al. (2000) define a search rule in the following simple way: “Let θ_i be the efficiency of the production recipe currently used by the firm, and let θ_j be the efficiency of a newly sampled production recipe; if $\theta_i < \theta_I$, the firm adopts $w_j \in \Omega$ in the next time period; if $\theta_i > \theta_I$, the firm keeps using w_i.”[15]

Setting Up a Model

2.1. Design Without Final Goals and Satisficing

It well might be that the greatest advantage a passage from the mainstream microeconomic tools to NK based modeling has, is in the possibility the latter gives to analyze agents with different levels of rationality. Indeed we can hope for a whole range of models of heterogeneous agents with *tunable rationality levels* to emerge on the existing bases. Rationality is however a notion that has many faces.

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[13] **Kauffman, Stuart; José Lobo & William G. Macready (2000)** *Optimal Search on a Technology Landscape,* Journal of Economic Behavior & Organization, vol. 43, *page 146*

[14] **ibid.,** *page 144*

[15] **ibid.,** *page 149*

The Simon-inspired research on decomposable systems and modularity that Frenken, Marengo and their colleagues have engaged themselves into recently, opens up one of those *faces*.

What they are interested in is the question of how the agents are to design a search heuristic other than a mechanistic optimizing in order to economize on time resources. Despite the fact that *satisficing* strategies by no means guarantee reaching a global optimum, given that optimizing can guarantee that only through an exhaustive search of all the possible configurations, an astronomic number even for relatively simple systems, very often the ends do not justify the means.

Frenken *et al.* (1999) introduce a notion of a *satisficing threshold* that stands for the percentage of a permissible deviation between the efficiency of the end-configuration achieved through a satisficing strategy and the globally optimal solution. Frenken (2001) brings the following example: “Thus, when [the satisficing threshold is equal to] 0.10 the satisficing search strategy accepts all strings that have fitness equal or higher than ninety percent of the fitness value of the global optimum”.[16]

While Frenken and his colleagues deal with the “trade-off between time-efficiency in search and the fitness of the string with highest fitness”[17], and their conclusions are that “strategies that aim to find the string with highest fitness are not necessarily most successful”[18], in this paper we turn out attention to a step-by-step process of technological and organizational change itself.

Instead of considering a *satisficing threshold* as referred to the efficiencies of only the final results of the search procedures, we shift our attention to *error thresholds* in accepting each and every decision, since, to turn the argument upside down, if there are no final goals, and each seemingly final result is just a step in a never-ending process, then every little step can be seen as leading to a final result in itself, to which a satisficing threshold idea can just as well be applied.

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[16] **Frenken, Koen** (2001) *Understanding Product Innovation using Complex Systems Theory.* Unpublished Academic Thesis. University of Amsterdam, *page 76*

[17] **ibid.**, *page 82*

[18] **ibid.**, *page 82*

It is quite plausible to assume that even if the agent can perfectly estimate the current efficiency of the employed technological configuration, in the face of uncertainty, the corresponding efficiency of the neighboring technological configurations to which a shift can be made at that point in time, can only be known imprecisely.

We can further notice, that the magnitude of imprecision in estimating the efficiency of the configurations belonging to that adjacent set is negatively related to the cost of such estimating procedure, and the time needed to conduct it.

In this way, reinterpreting the idea of Frenken and his colleagues, an error threshold can be roughly defined as the acceptable deviation of the observed efficiency of a technological configuration to which a shift can be made in each given period, from the real efficiency of that configuration.

In this light the imprecision in agents' decision making schemes can be seen both as intentional and unintentional:

- The intentionality of such imprecision is characterized from the one side by the desire to avoid the rigidity trap through experimentation, and from the other, by the desire to economize on the costs of the adjacent technological configurations' evaluating process.
- The unintentionality of it, however, is characterized by the bounds on human rationality and computational skills.

2.2. Rigidity, Experimentation[19] and Imprecision

It has been long noted by economists and not only that "it is better to be roughly right than be precisely wrong", and it indeed makes perfect sense. However, looking at some business data we are sometimes inclined to reformulate that saying claiming that "it is sometimes better to be *roughly right* than to be *right precisely*"!

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[19] Auerswald *et al.*(2000) talk about experimentation as well. However, they understand the mutations themselves as experiments, while in this paper I call experimenting the strategies of deviation from the rigid rule of accepting only technologies better in the short-run.

Unlike the former, this claim may seem to be paradoxical, and indeed in economics it is mainly treated as marginality, and not taken into consideration. The family of NK-inspired *landscape models*, including the papers by Frenken, Marengo and their colleagues, are also neglecting this phenomenon, in what, once the firm has *tried* a position different from the one currently employed, and identified it as an inferior, it wouldn't shift for sure, and, moreover, that trial will be assigned a zero value.

Now, this is limiting the model in two ways. First, even if the trial resulted in failure, the firm actually gains some knowledge in the process, and hereafter, can use that knowledge, the option created but not used at that time, in the future.

Kaplan (1986) brings an example that accentuates the impact of past decisions on the future options, as well as the matter of uncertainty over future opportunities to innovate. He writes that the returns on the initial investments (the value created) in automatic and electronic machine tools made by many firms in 1970s were quite insignificant. The conventional measures would have naturally filed those investments as failures. However, when the microprocessors arrived in the early 1980s, these were exactly the firms that made the named initial investments that were by a margin superior in shifting to the new technology that brought about significant real profits.

Hence, the early investments made in the automatic and electronic machine tools have provided a platform in the form of the personnel's improved skills of handling the new techniques, lower costs of shifting to microprocessor-based technologies, organizational structure better framed for adoption of this novelty, for the subsequent investments, while the companies that earlier have deferred investing have lagged behind.

Another example can be found in Stacey (1992)[20], where he writes about how the failure of *Sony* with the 8-cm *Discman*, combined with the lessons learnt from the *Betamax* standard failure, did actually allow the firm to launch successfully the *Data Discman* product in 1991.

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[20] **Stacey, Ralph (1992)** *Managing Chaos: Dynamic Business Strategies in an Unpredictable World,* Kogan Page, London, *pages 15-17*

The second interesting point of view on how the trials can improve the functioning of a system, even if they have no rational basis at all, is expressed by Brown & Eisenhardt (1998)[21].

They write about how the Naskapi people of the North-Eastern Labrador fight for their survival in that unfriendly environment they live in, through caribou hunting. Many generations long experience provides them with good knowledge of the hunting tactics. Nevertheless, they experiment:

> Most days, the Naskapi relied on the experience of the senior hunters in the band. But in times of high uncertainty, when game had been particularly scarce, the Naskapi set aside their experience and turned to magic. […] So the hunter-dreamer cradled a shoulder blade from a long-dead caribou, attached it to a stick, and put it over a campfire. The band patiently waited for cracks to appear and then hunted in the direction of the cracks[22].

That seems like a completely irrational way of decision-making. But, in reality, it did help them to survive, because exactly through those random trials, the Naskapi people could learn about the new hunting grounds, the ones that would have remained untried if they had persisted in following their experience all the time. So, sometimes it just pays to go downhill a bit, something that a pure *NK* model prevents us from doing.

Finally, apart from the intentional imprecision the agents might desire in order to avoid falling into the trap of rigidity, if we at all talk about limits on rationality, we do have to consider as well, that the agents can just be wrong in estimating the efficiency of the potential configurations to which a shift might be made.

Indeed, it is hardly plausible to accept an idea of the agents possessing enough computational and analytic skills to be able to know with absolute precision how good is the technological or organizational configuration, which has not yet even been tried in practice.

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[21] **Brown, Shona L. & Kathleen M. Eisenhardt (1998)** *Competing on the Edge: Strategy as Structured Chaos,* Harvard Business School Press, Boston, MA., *pages 95-98*

[22] **ibid.,** *page 96*

2.3. A Simulation Model

Is there a formal way to treat the phenomena discussed in the previous section? Is there a way to formally compare the rational and the not-so-rational agents in various business environments?

We suggest here that the original framework of the NK model can easily be reformulated for that purpose. As it was noted before, in the original model, the new configuration w_j is adopted instead of the current one w_i if and only if $\theta_i > \theta_i$, where θ_j is the efficiency of a newly sampled production recipe, and θ_i is the efficiency of the production recipe currently used by the firm.

Let us instead consider that the firm can observe perfectly only the efficiency of the currently employed technological configuration, θ_i, while observing some hypothetical level of efficiency $\bar{\theta}_j$ instead of the real value θ_j, with:

$$\bar{\theta}_j = \theta_j + \chi\varepsilon \qquad (7)$$

where ε is random normally distributed in [-0.5;0.5], and χ is a tunable parameter measuring the degree of imprecision (either intentional or unintentional) of the agent's estimation of the new configuration's potential efficiency level. The extreme case of $\chi=0$ reflects a perfectly rational and rigid agent as in the original model, while, on the opposite, a case of $\chi=1$ reflects a situation when the observed efficiency of a new configuration is maximally random.

Then, the agent would adopt a new configuration if and only if $\theta_i < \bar{\theta}_j$. The mean value of ε is 0, so that on average the firm observes the real value of each possible configuration, however given that $\theta \in [0,1]$, and given the randomness of ε, the modification of the model would lead to cases when for the values of $\chi \neq 0$ and increasing towards $\chi=1$, the agent is more and more likely to either reject a configuration that is more efficient than the current one, and, more importantly, to accept configurations moving it “downhill”. It is assumed that once the new configuration is accepted, its true efficiency level becomes perfectly observable for the firm.[23]

Due to a restriction that the efficiency cannot be negative or have a value of more than the maximum of 1, the algorithm of the model on which the simulations are run is written in such a way to assign a value of 0 for all the values of $\bar{\theta}_j < 0$, and a value of 1 for all $\bar{\theta}_j > 1$.

2.4. Simulation Results

The simulation analysis of the above mentioned extension of the NK model was conducted using the Lsd simulation language designed by Marco Valente.[24]

For all the simulation runs the value of N was kept constant equal to 20, while the value of K varies from 0 to 19. The value of χ varies for each K in the range [0, 0.5] with an interval of 0.025 to account thus for the probability of making a mistake in evaluation of the efficiency of the new configuration in the range between 0% and 50% in each direction.[25] For each value of K the simulation was run 10 times, with different seeds. The efficiency of each strategy was computed as the average over the efficiency obtained by each of the 10 agents employing it. Hence for each combination of K and χ, 100 observations were obtained. Due to physical limitations, the *never-ending* process of technological and organizational change was “stopped” at 5000th step.

The results of the simulation runs are generalized in the four graphs below showing the optimal values of χ, and the highest values of χ still superior to the χ=0 case both for the final 5000th step of the simulation run, and averaged over all 5000 steps[26]. More detailed, case-by-case graphs are presented in *Appendix 2*.

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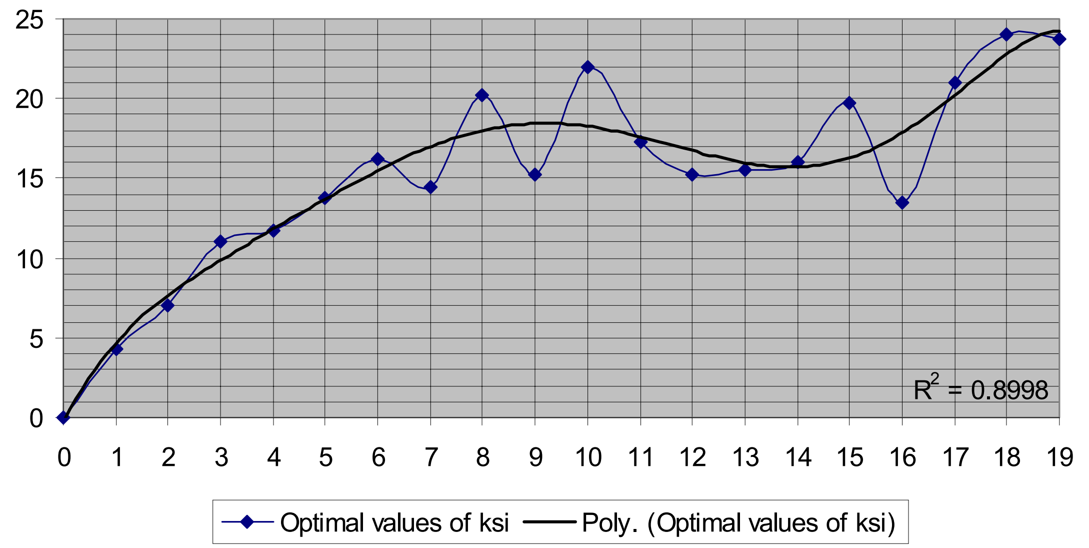
[23] Different updating rules are planned be explored in the future research instead of that simple one.

[24] The Lsd package including the original NK model is available for free download from: http://www.business.auc.dk/lsd/. The code for the modified model is available from the author. I would like to thank Marco Valente for his great help in writing the model in Lsd.

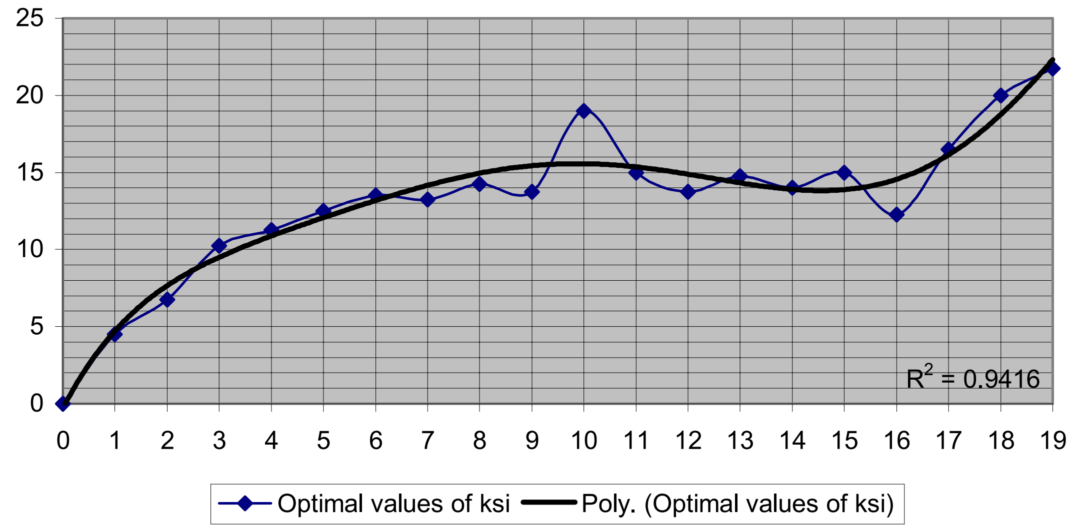
[25] Larger values of χ were not taken into consideration for the reason of their being clearly inferior for each K.

[26] See *Appendix 1* for the explanation of the graph construction mechanism.

Graph 1: Optimal values of *ksi* *(period 5000)*



Graph 2: Optimal values of ksi *(average over 5000 periods)*



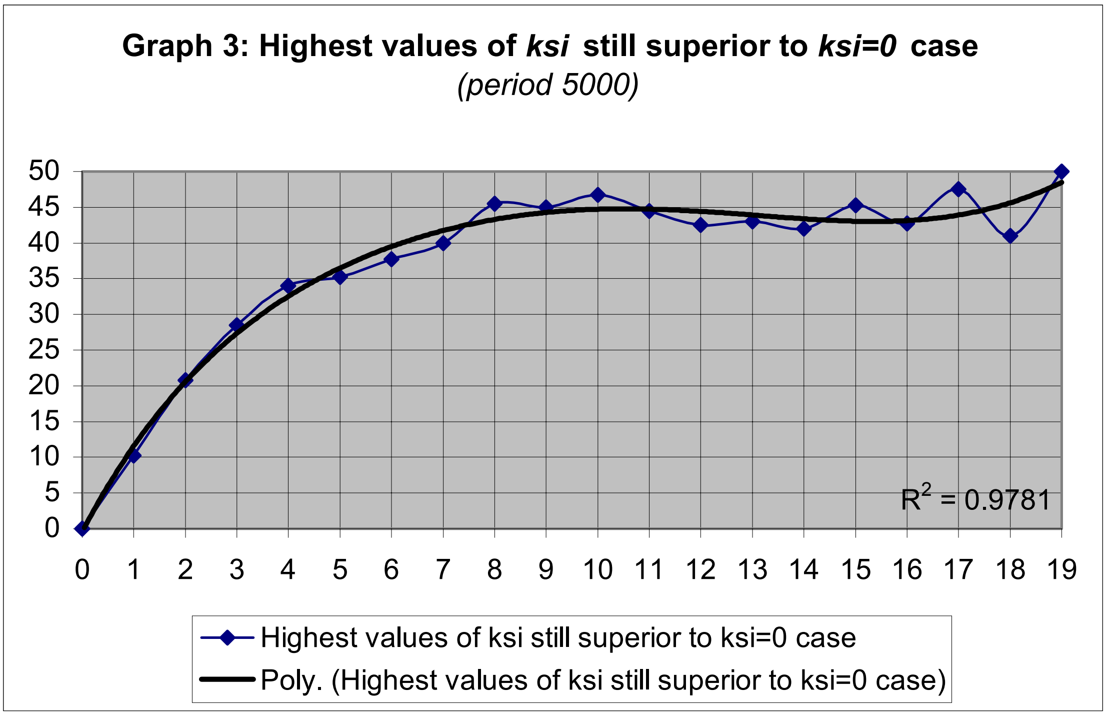
The first striking result of the modified model is that for no values of K, apart from the uninteresting case of K=0, is the perfectly rational rigid behavior (corresponding to the case of χ=0) optimal.

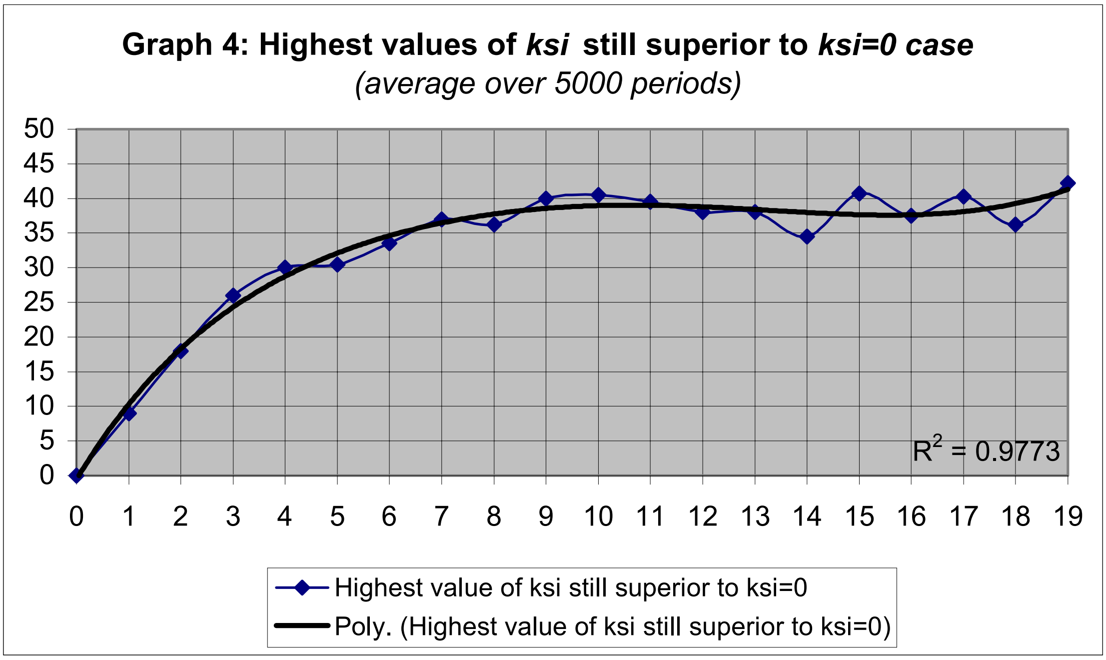
As it can be seen from the table and the graph above, only for the cases of low complexity, corresponding to low values of K, is the optimal level of χ relatively low. The phase transition between the cases of low and high complexity, apparent in the original Kauffman's model (1993) is present in the modified model in a much less pronounced way. The case of K=0 can be seen as best corresponding to the purely neoclassical unconnected systems, leading not surprisingly to superiority of a perfectly rational behavior. However, the high levels of χ for the major part of the values of K tell us how marginal indeed is the purely neoclassical equilibrium.

It can also be seen from the corresponding case-by-case graphs (see *Appendix 2*) that while for the low and average values of K a rather smooth one-peaked correspondence between the levels of χ and values of K can be observed, such correspondence is getting more and more blurred for the cases of very high complexity.

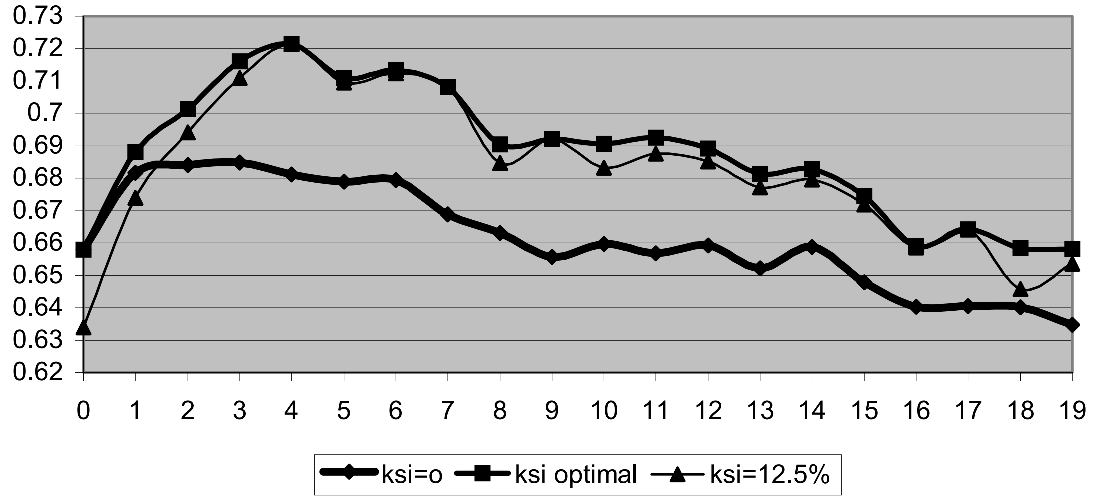
Another way to show how large indeed can the imprecision be with still "mistake-making" being a better business strategy than perfectly rational behavior is presented in the *Graphs 3 and 4*, where for each value of N, the highest value of χ is shown with the average efficiency obtained utilizing the satisficing strategy still higher than the corresponding efficiency of the perfectly rational strategy.

These graphs confirm the previous results. The range of the levels of χ superior to a perfectly rational behavior is extremely wide for most of the values of K, which can be easily noticing that this range corresponds to the whole area below the graph. This is an important result in itself, suggesting that the agents do not have to be precise in their imprecision level, and hence, no super-rationality is required in adopting such heuristic.


Graph 3: Highest values of *ksi* still superior to *ksi=0* case
(period 5000)
0
5
10
15
20
25
30
35
40
45
50
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19
R^2 = 0.9781
Highest values of ksi still superior to ksi=0 case
Poly. (Highest values of ksi still superior to ksi=0 case)


Graph 4: Highest values of *ksi* still superior to *ksi=0 case*
(average over 5000 periods)
0
5
10
15
20
25
30
35
40
45
50
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19
R^2 = 0.9773
Highest value of ksi still superior to ksi=0
Poly. (Highest value of ksi still superior to ksi=0)

Finally, an interesting perspective opens up when we look at *Graph 5* below. Here, the average values over 5000 periods are given for some values of χ. What the graph shows is the comparison of the performance of the agents employing the search heuristic of the original model ($\chi=0$), a chosen search heuristic with a positive value of χ ($\chi=12.5\%$), and the "super agents" that are able to tune their parameter χ to each of the levels of complexity, given by the parameter K, so that to attain the optimal fitness in each of those cases (χ optimal).



Graph 5: Average Fitness over 5000 periods for some values of *ksi*

What is interesting here is not only that the graph confirms the previous results; this had to be the case for obvious reasons. The interesting observation can be made comparing the behavior of from the one hand the line representing the $\chi=0$ case, and, from the other, the lines representing the remaining two cases.

As in the original Kauffman's model, after a very short initial increase in the average fitness, with the growing complexity of the system, its value steadily declines. This result was taken to suggest that the agents have to work on decreasing the complexity of the system through different mechanisms in order to hope for a better overall performance.

Now, this is not at all necessarily the case if we take the value of χ positive. For both of the remaining two cases in the graph, the initial growth is much longer and much steeper, especially so for the more representative case of χ=12.5%. Reaching its maximum at K=4, the average efficiency remains pretty high for the values of K up to K=7, and does not go below the case of K=0 for no values of K, however large it is. On the other hand, for the case of χ=0 for all the values of K between [9;19], we observe the average fitness lower than that the agent attains in the completely unconnected system, that a K=0 case represents.

This is important in two ways. First of all, the mechanism that the agents can design in order to decrease the complexity of the system are costly, and hence *ceteris paribus* are not desirable. Now, using a scheme with a positive value of χ, apart from the other pluses, discussed above, thus, lowers that cost just as well. Secondly, the so-called *new economy* calls for an increased emphasis that has to be put on the cases of average and high complexity, exactly where the search heuristics employing positive values of the parameter χ are performing especially good compared to the case of the original setting of the model.

Generalizations and Discussion

There are several points of possible concern that can be raised regarding the above model modification, and in this section I would try to discuss some of them.

First of all, one might ask, what actually does the trick? In the modified version of the new configuration adopting rule, the factor of randomness seems to play a major part. The mechanism seems to be very reminiscent of the *simulated annealing* principle, well known in the literature on genetic programming[27].

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[27] I would like to thank Koen Frenken for bringing my attention to this point.

In fact, some of the literature on business case studies that served as the staring point for the current paper indeed give a lot of attention to randomness as the surprising force helping to run the business better. Such are the examples in Brown & Eisenhardt cited above.

However, my belief, and my aim in this paper was not to accentuate the role of randomness in decision making. The main point was to see how true indeed is the proposition of Simon on *deliberate experimentation* as the guiding force in decision making when facing a complex changing world where no goal is ultimately final.

To check whether random variable actually does play a role, a slight modification of the model was developed, in which randomness was absent. It was noticed that while in the model modification presented above the errors in precise estimation of the relative efficiency of the novel technological configurations could have been both in the sense of accepting a configuration that in fact was inferior to the currently employed one, or rejecting the ones in fact superior to it, the whole idea of experimentation as the guiding force suggests putting more emphasis towards the so to say "optimistic" errors.

Rejecting what might have been a better way of running the business just does not seem to be a good an idea intuitively. So then, would it be right to say that this is exactly the acquired option of accepting modifications even if they are slightly inferior to the present state of affairs that makes the difference?

The preliminary results of the simulation runs show that this is indeed the case. What was changed is again the mechanism of accepting or rejecting new adjacent configurations. Instead of the one used above, the following rule was suggested: accept a new configuration w_j instead of the currently employed configuration w_i if and only if $\theta_i < \bar{\bar{\theta}}_j$, where[28]:

$$\bar{\bar{\theta}}_j = \theta_j + \chi/2 \qquad (8)$$

---

[28] $\chi/2$ is taken instead of χ to account for the same magnitude of the effect when we change from a stochastic to a deterministic case.

The results of the simulation runs of this modified setting of the model are extremely similar to the ones discussed above both in terms of the optimal level of χ, and the highest levels of it still superior to the case of $\chi=0$.

This suggests that this is not the randomization of the strategy, and neither the fact of mistake-making *per se* that is responsible for the results discussed above, but indeed it is the case that overly rigid structures of the perfectly rational optimization technique just do not let the decision maker gain from the advantages a more flexible scheme of a dynamic, experimenting decision making provides.

Another concern might be raised in this respect. It could be the case that omission of such factor as the *search costs* can benefit overly explorative activities, while a modification of the model to a one that accounts for those costs would also allow a conservative strategy of accepting only the configurations by some fraction superior to the current one becoming a winning one.

This is a more difficult concern to answer to, because of the difficulties of directly measuring such costs in the present algorithm of the model. Nevertheless, some conjectures can still be made in this respect. First of all, it has to be noted that search costs can be classified in two major groups:

- The shifting costs between the two adjacent technological or organizational configurations
- The costs of actually estimating whether such change is desirable.

Now, with no doubts, the search heuristic applied in the present modification of the model calls for an increase in the first group of the costs. Experimenting means more often changes, and hence more resources have to be directed towards *shifting costs*. The magnitude of that increase can be measured in the simulation runs by the *successful mutations* parameter. And it does increase substantially when we move from the case of $\chi=0$ to positive values of χ.

Thus, depending on K, for its high enough values, the search heuristic corresponding to the optimal values of χ presupposes about 10-30 times more shifts that the case of $\chi=0$, and hence, the overall shift costs should be significantly higher.

However, this is not as alarming as it might seem. The thing is that for high enough values of K, the optimal value of χ is between 15-25% in both directions, which accounts for the double of that values range of desired imprecision. But then, as it has been noted above, that imprecision is a way of economizing on the costs of evaluating the relative efficiency of the yet untried adjacent technologies.

Thus, while dragging the shifting costs up, such search heuristic lowers significantly the calculation and estimation costs. Measuring the relative magnitude of these two effects unfortunately is an unsolved problem yet, but the fact that we are considering here the day-by-day small organizational and technological shifts, which are not great in magnitude, leaves us to think that the costs associated with such shifts should not be too high, and should well be balanced by the decrease in the presumed precision in estimating the yet unknown.

Consequently, one might ask, why do the agents necessarily have to stick to some given magnitude of imprecision, rather than trying to tune that parameter in accordance with the level of the complexity of the system?

Indeed, as it has been noted in the discussion of the *Graph 5* above, the "super agents" able to do so apparently perform better than the agents applying any other given search scheme. So, in a way the model restricts the possibilities of the agents. Quite obviously, a simpler system calls for more rigid scheme, because of the tradeoff between the costs of rigidity (low in this case) and the possibility it gives to reach a higher level of efficiency, and that scheme has to become more and more flexible with an increase in the complexity.

Moreover, the possibility of tuning the parameter χ is an important advantage in other, probably even more important respect. With the evolution of technology, different and quite distinct phases change each other. Apparently then, different values of χ would be optimal depending on whether the agents are in the phase of fast and booming development of the given technology, or the technology is mature, and only slight and slow changes are being made to it.

This is an important topic for the future development of the current model.

Finally, a concern might be raised regarding the question of why don't the agents change the state of several elements at the same time. One of the reasons of not including that possibility in the model is that what I was focusing the attention on are the small day-by-day decisions, and especially since the agents are given possibility to deviate from the rigid rule of accepting new technological configurations proposed in earlier papers on the subject, a change in the state of more than one element at a time was not seen important. From the other hand, Auerswald *et al.* (2000) confirm the intuition that an effect "taking bigger steps on a given landscape" has is "like walking with smaller steps on a more rugged landscape."[29] So then, because we consider here the landscapes of all the possible levels of ruggedness, introducing a possibility of taking larger steps would just mean doing a double work, without expecting any new results.

Conclusions

The results obtained through simulation analysis of the model can seem to some as very surprising and questionable, while the others might think of them as overly trivial. Here, I would like to concentrate on the questions of why did we get the results that we get, what is a logical explanation, why should not they have to be treated as marginality, and why they are not as trivial as it might seem?

The part that can be seen both not trustworthy or trivial, depending on from where to look at it, is that the results confirm the intuition that satisficing can be optimal to rational optimization even if we do not consider the costs of being rational at all. I have tried to avoid in the most part the reference to rationality, operating more with the terminology like myopic rationality, precision and rigidity. That was made for the reason that I doubt that there is indeed any definition of what is to be considered as rational, accepted by all the scientists. Indeed, if we remember the Rosenthal's *Centipede Game*, we might ask if the agent who gets in the end a hundredth of what she might have got be she less rigid in following the rule of backwards induction, is indeed rational? Well, pure

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[29] **Auerswald, Phillip; Stuart Kauffman, José Lobo & Karl Shell** (2000) *The Production Recipes Approach to Modeling Technological Innovation: An Application to Learning by Doing,* Journal of Economic Dynamics and Control, 24, *page 427*

neoclassical economist has to admit that she is, while simple human logic dismisses this conclusion.

So, what does it mean to be rational[30]? If being rational in the framework of the NK model means that the agent possesses knowledge of all the possible positive and negative effects any change in any parameter of the system can have, then yes, no satisficing scheme of any kind can beat it. But, then, this is simply impossible. If, on the other hand, being rational means following the backwards induction rule as in the *Centipede Game*, then, rationality is clearly inferior.

It is much more transparent to operate with notions such as rigidity or precision. Indeed, the disadvantages of being overly rigid are quite obvious, while being precise has its own disadvantages just as well. In a newspaper article I read a while ago it was discussed how people turn back from the high-precision all-autonomous housing plans, to the more conventional ones. The reason was in that the hi-tech insulation of the walls and windows led to very substantial increase of allergies the owners of those houses acquired. Now this is exactly the same with precise search schemes, where the imposed precision of the rule being followed lead to the case where the tiny "viruses" that once were introduced (even if not intentionally) in the scheme, are not given a chance of leaving the system ever after, and ultimately result in its failure or stagnation.

Very important are also the results obtained from the observation of the *Graph 5* that cast some doubts on almost uniform agreement between the economists that it is worth for the agents to work on decreasing the complexity of the system, even if it is associated with quite high costs. In reality, apart from the negative effects that the increased complexity has on the efficient functioning of the system, it brings about substantial positive effects that outweigh the former effects at least in the initial phase of such increase. The intuition behind this result is quite simple. In a completely unconnected system, just as in the system with very low level of connectivity between the elements, it is not possible to capitalize on the positive effects of such connections. Indeed, while the connections between the elements are almost unanimously considered

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[30] For a more in-depth discussion on the advantages and disadvantages of being rational (in different interpretations of that term) see: **Hovhannisian, Karen (2000)** *To be or not to be Rational?* Mimeo, University of Siena

as harmful, it is not very often noted that the side-effects such connections bring about can be positive just as well as they can be negative, and thus, an increase in efficiency of some elements can be obtained with no additional cost or effort, just by changing the state of an element it is connected to in some way. So, the positive externalities of such connectedness can indeed outweigh its negative effects for quite some region of complexity of the system under consideration.

In the end, remembering once again Simon's idea on design without final goals, I would like to note that the model discussed in the current paper is by far not meant to be considered such a final goal. On the contrary, my belief is that NK-inspired research is able to give much more important and general results if we note that probably the greatest advantage it provides us with is in the fact that here, unlike either the mainstream neoclassical theory, where too much stress is put on rationality and intentionality, or the "mainstream" evolutionary economics, where the agents too often are seen as possessing rationality of an amoeba, we are able to bring comparisons between agents possessing different levels of rationality, and putting them in different environments, get the idea on how much rational it is indeed worth to be in this and that circumstances.

Appendix 1: Explanation of the graph construction mechanism

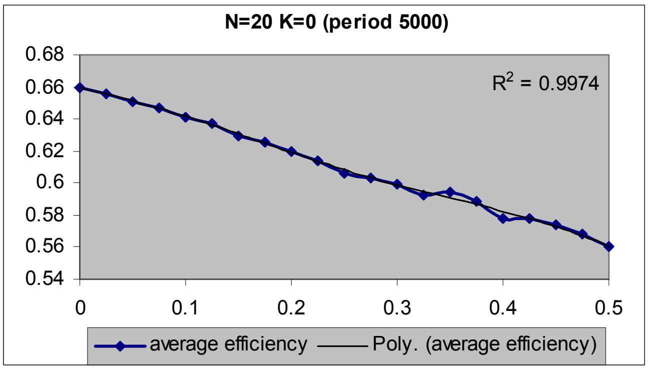
The data gathered from the simulation runs using the Lsd program was subsequently processed using Microsoft Excel program to obtain the desired graphs. The case-by-case graphs presented in the *Appendix 2* below show the crude graph of the actual data together with the corresponding trendline. The polynomial trendline was necessary to use to smooth the line, because of the substantial role random variables play in getting the final data.

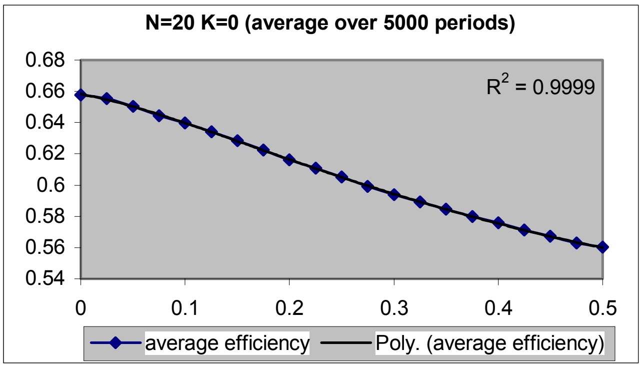
The polynomial trendline of the order six that was used, is obtained by calculating the least squares fit through points by using the following equation: $y = b + c_1 x + c_2 x^2 + ... + c_6 x^6$, where b and $c_1 \dots c_6$ are constants. Each graph contains the R-squared value of the fit of the trendline to the actual data, with its high values showing that the use of the trendline is indeed justified.

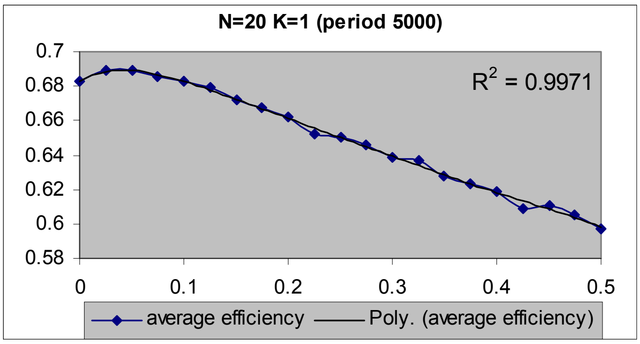
The *Graphs 1-4* in the main text of the current paper are subsequently constructed using the corresponding optimal and still-superior to the case of χ=0 values of the parameter χ. Those graphs also contain polynomial trendlines obtained in the exactly same manner as shown in the previous paragraph for the case-by-case graphs. The corresponding R-squared values are also shown on the graphs.

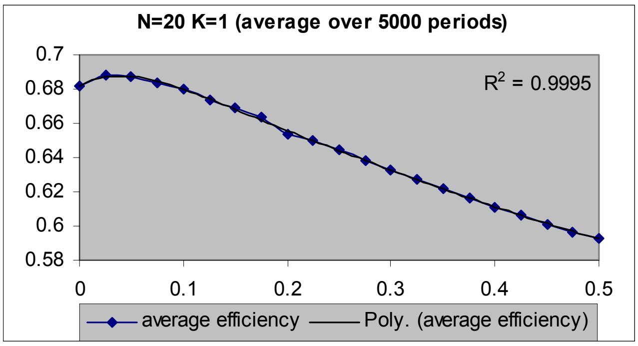
Graph 5 represents the actual data on the maximum fitness obtained for each of the three cases and for each of the values of the parameter K. The χ-optimal line is drawn on the basis of the observations of the maximum fitness obtained for each of the values of the parameter K, regardless of the corresponding value of the parameter χ.

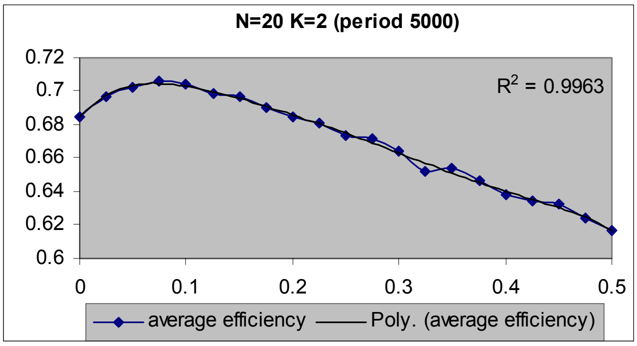
Appendix 2: Case-by-case Graphs

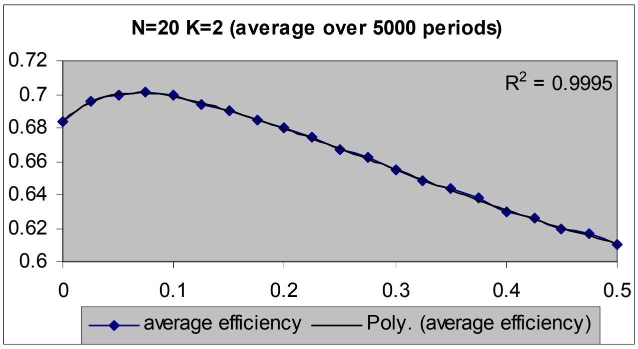


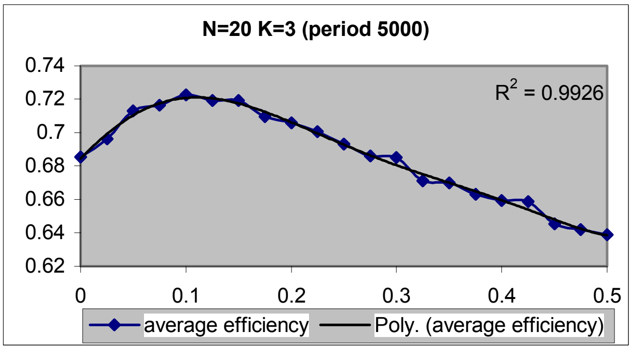


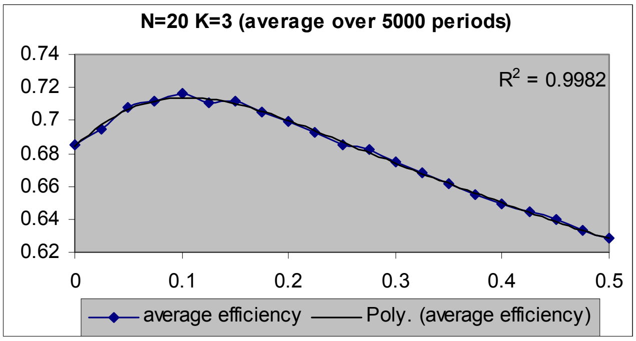


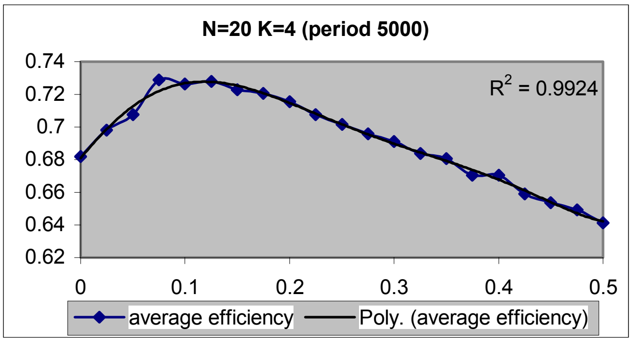


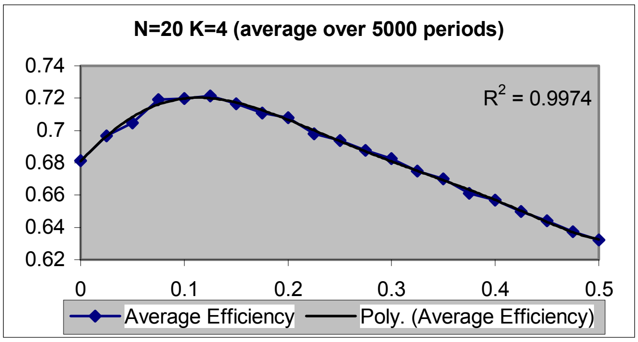


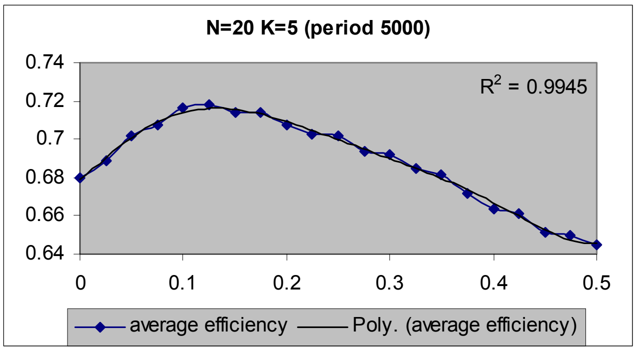


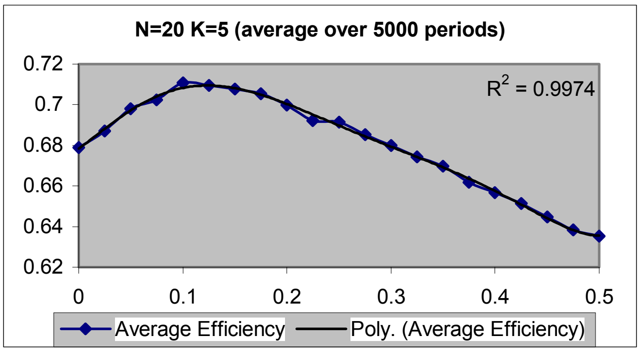


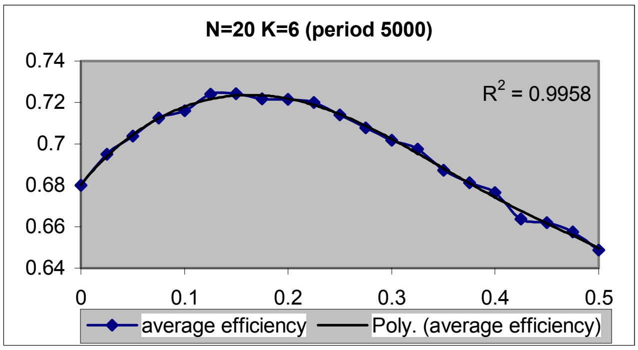


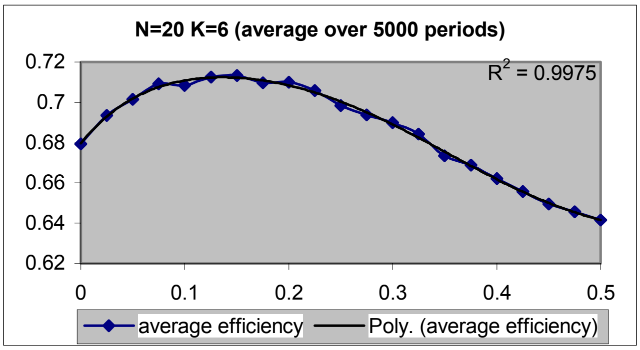

N=20 K=4 (period 5000)
0.74
0.72
0.7
0.68
0.66
0.64
0.62
R^2 = 0.9924
0
0.1
0.2
0.3
0.4
0.5
average efficiency
Poly. (average efficiency)

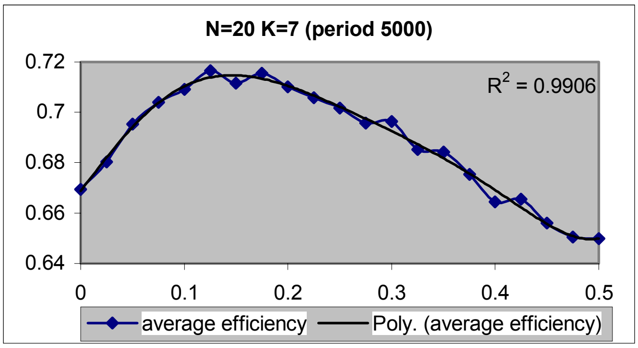

N=20 K=4 (average over 5000 periods)
0.74
0.72
0.7
0.68
0.66
0.64
0.62
R^2 = 0.9974
0
0.1
0.2
0.3
0.4
0.5
Average Efficiency
Poly. (Average Efficiency)

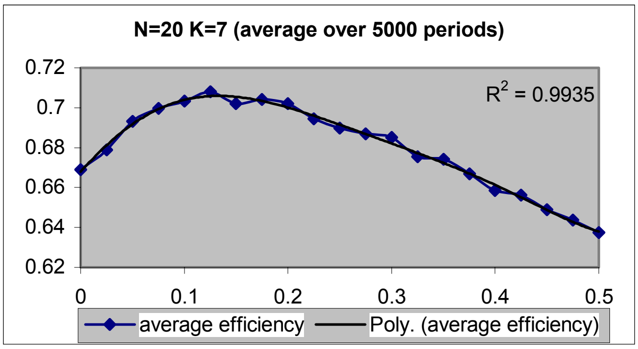

N=20 K=5 (period 5000)
0.74
0.72
0.7
0.68
0.66
0.64
R^2 = 0.9945
0
0.1
0.2
0.3
0.4
0.5
average efficiency
Poly. (average efficiency)

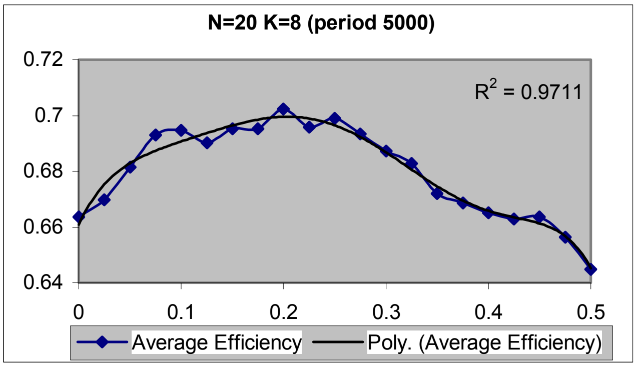

N=20 K=5 (average over 5000 periods)
0.72
0.7
0.68
0.66
0.64
0.62
R^2 = 0.9974
0
0.1
0.2
0.3
0.4
0.5
Average Efficiency
Poly. (Average Efficiency)


N=20 K=6 (period 5000)
0.74
0.72
0.7
0.68
0.66
0.64
R^2 = 0.9958
0
0.1
0.2
0.3
0.4
0.5
average efficiency
Poly. (average efficiency)


N=20 K=6 (average over 5000 periods)
0.72
0.7
0.68
0.66
0.64
0.62
R^2 = 0.9975
0
0.1
0.2
0.3
0.4
0.5
average efficiency
Poly. (average efficiency)


N=20 K=7 (period 5000)
0.72
0.7
0.68
0.66
0.64
R^2 = 0.9906
0
0.1
0.2
0.3
0.4
0.5
average efficiency
Poly. (average efficiency)


N=20 K=7 (average over 5000 periods)
0.72
0.7
0.68
0.66
0.64
0.62
R^2 = 0.9935
0
0.1
0.2
0.3
0.4
0.5
average efficiency
Poly. (average efficiency)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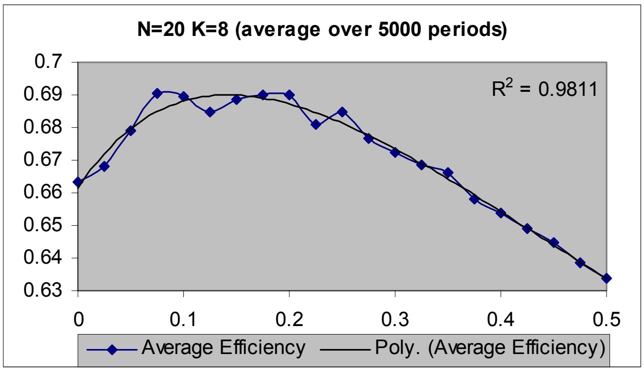
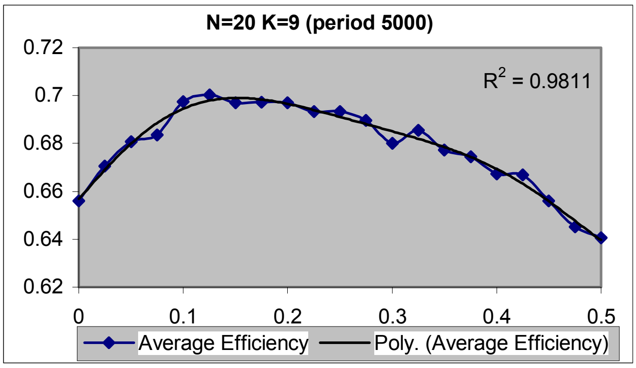

N=20 K=8 (average over 5000 periods)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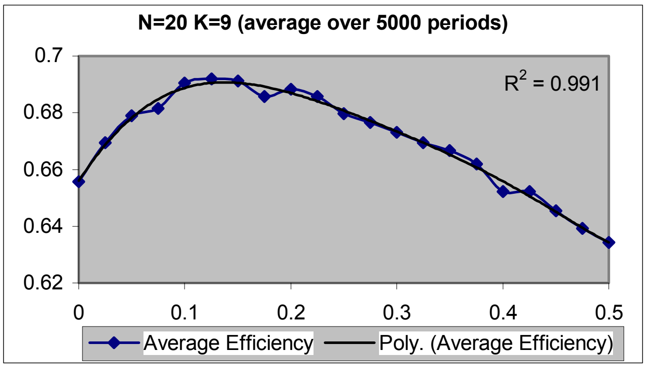
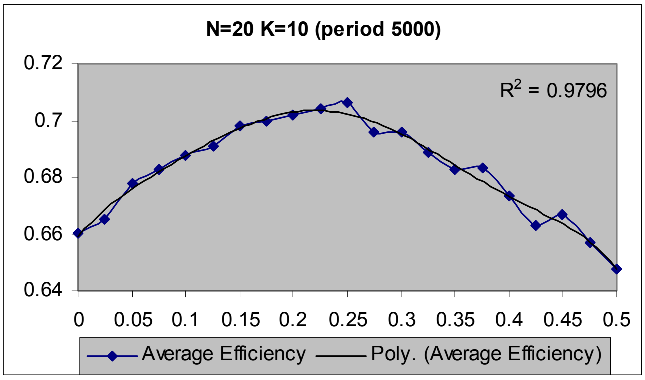
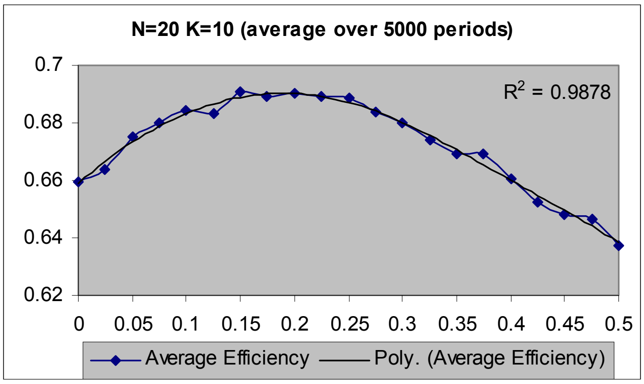
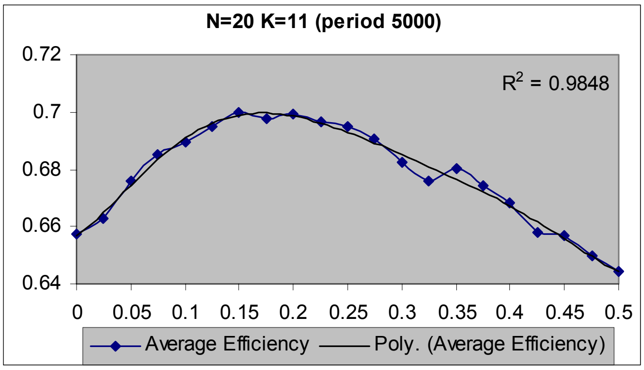
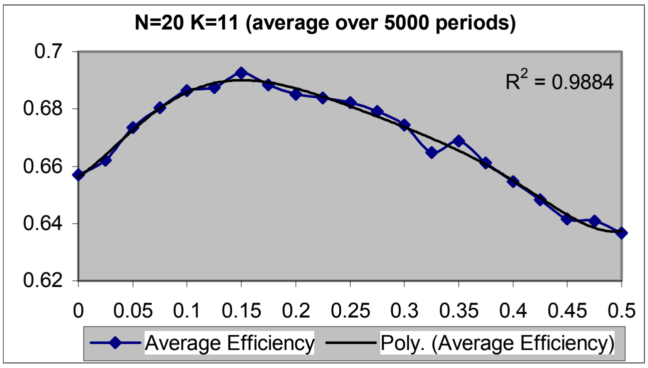
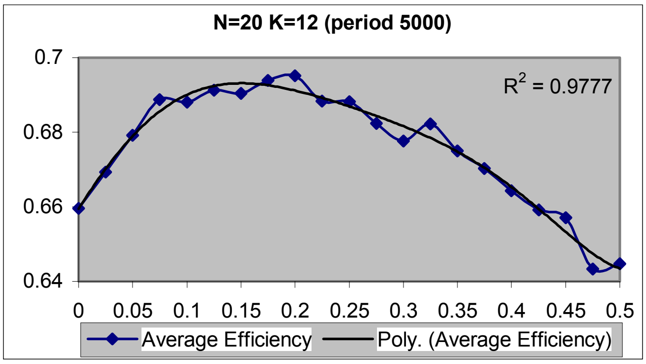

N=20 K=9 (average over 5000 periods)

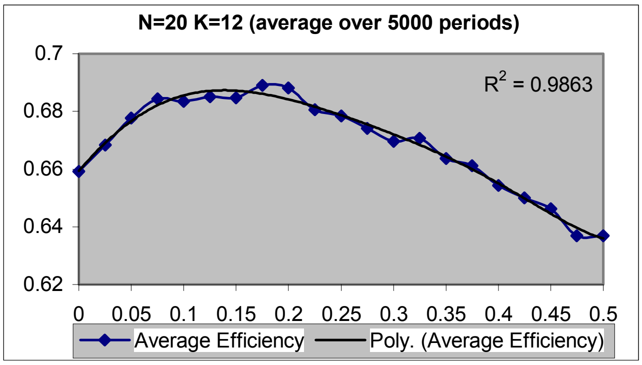

N=20 K=10 (period 5000)

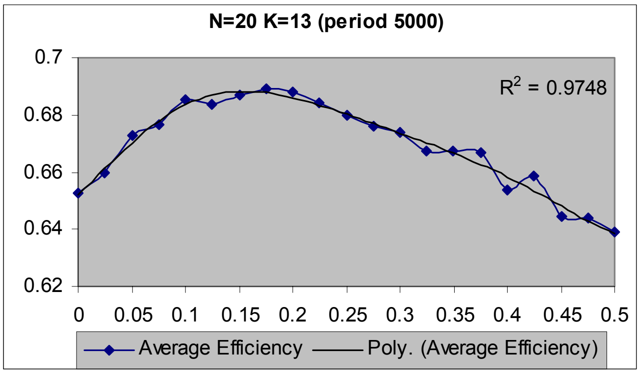

N=20 K=10 (average over 5000 periods)

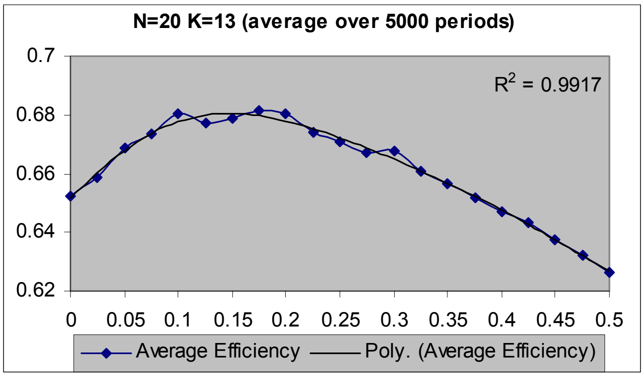

N=20 K=11 (period 5000)

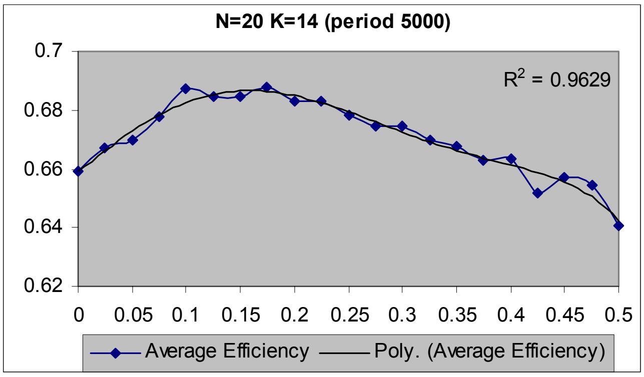

N=20 K=11 (average over 5000 periods)

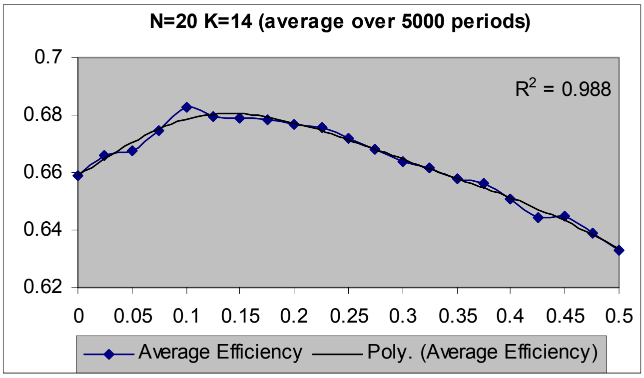

N=20 K=12 (period 5000)
R^2 = 0.9777
0.7
0.68
0.66
0.64
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

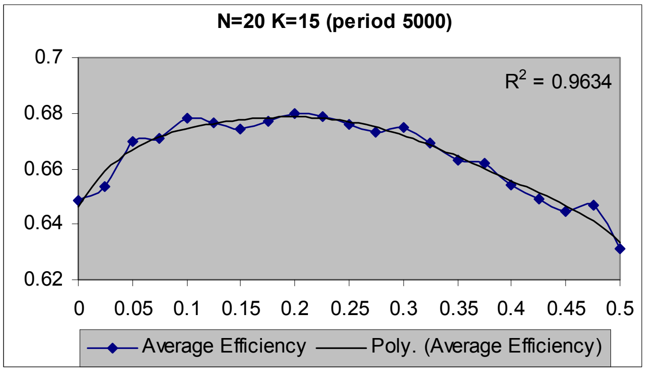

N=20 K=12 (average over 5000 periods)
R^2 = 0.9863
0.7
0.68
0.66
0.64
0.62
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

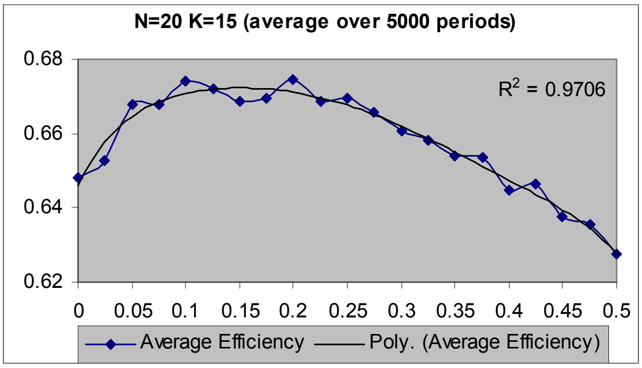

N=20 K=13 (period 5000)
R^2 = 0.9748
0.7
0.68
0.66
0.64
0.62
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

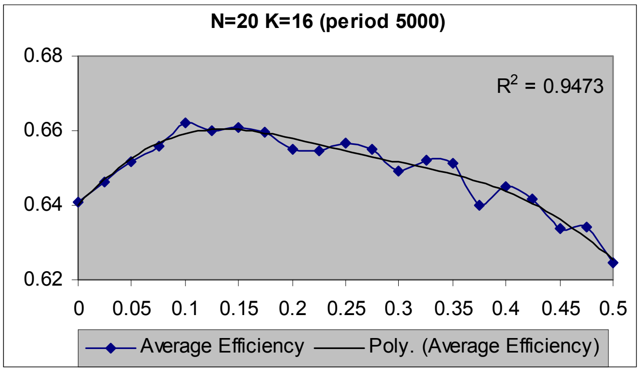

N=20 K=13 (average over 5000 periods)
R^2 = 0.9917
0.7
0.68
0.66
0.64
0.62
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

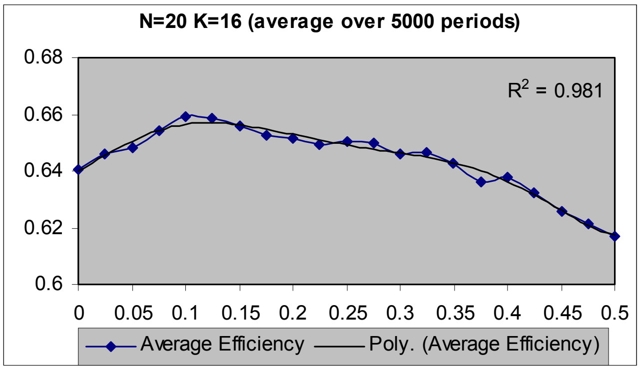

N=20 K=14 (period 5000)
R^2 = 0.9629
0.7
0.68
0.66
0.64
0.62
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

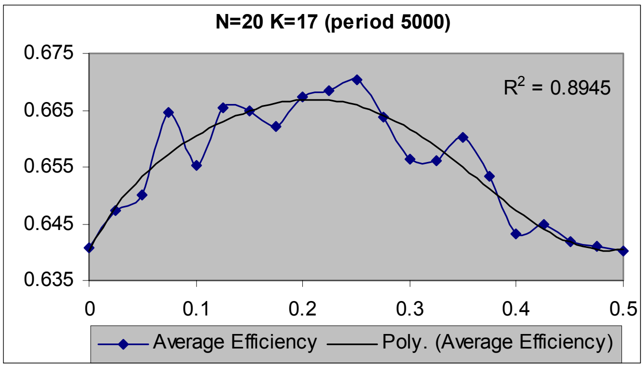

N=20 K=14 (average over 5000 periods)
R^2 = 0.988
0.7
0.68
0.66
0.64
0.62
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

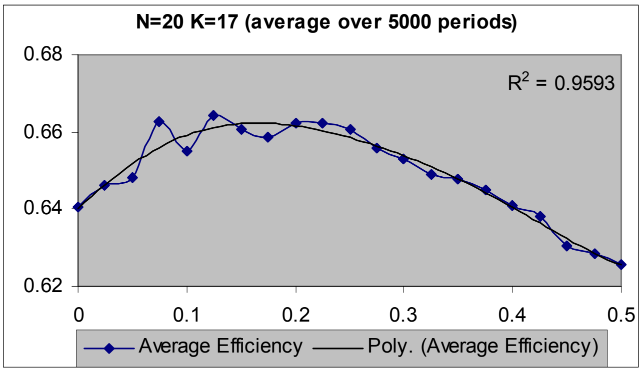

N=20 K=15 (period 5000)
R^2 = 0.9634
0.7
0.68
0.66
0.64
0.62
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

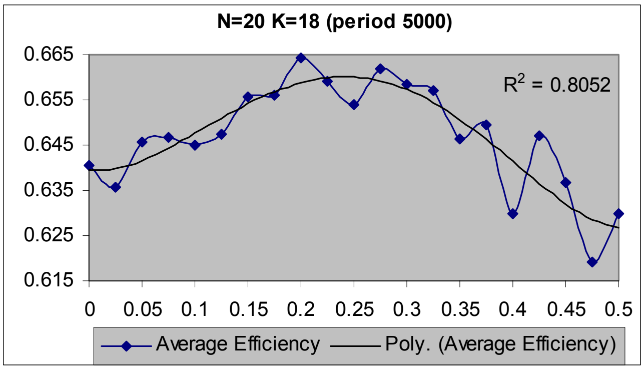

N=20 K=15 (average over 5000 periods)
R^2 = 0.9706
0.68
0.66
0.64
0.62
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

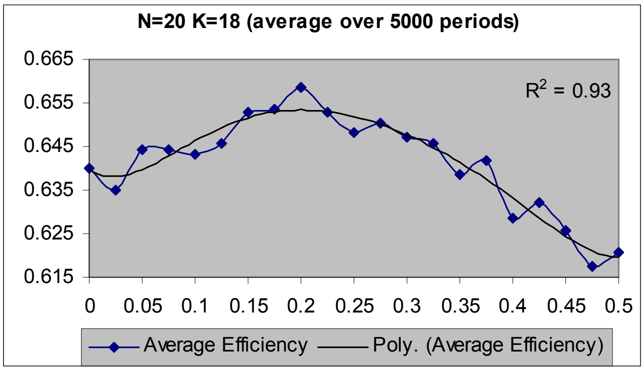

N=20 K=16 (period 5000)
R^2 = 0.9473
0.68
0.66
0.64
0.62
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

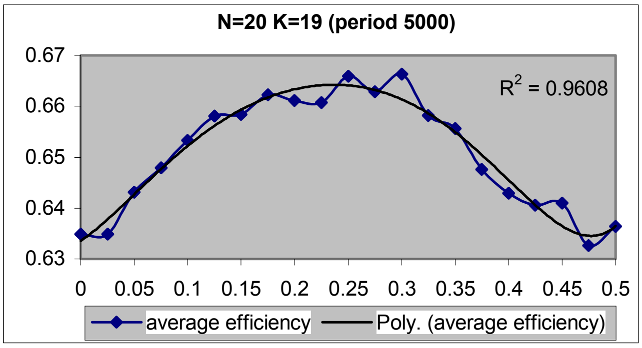

N=20 K=16 (average over 5000 periods)
R^2 = 0.981
0.68
0.66
0.64
0.62
0.6
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)

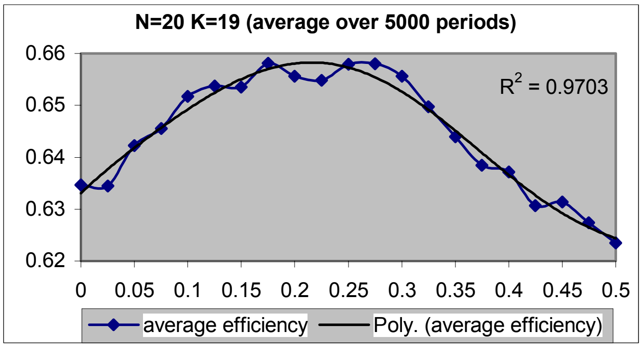

N=20 K=17 (period 5000)
R^2 = 0.8945
0.675
0.665
0.655
0.645
0.635
0
0.1
0.2
0.3
0.4
0.5
Average Efficiency
Poly. (Average Efficiency)


N=20 K=17 (average over 5000 periods)
R^2 = 0.9593
0.68
0.66
0.64
0.62
0
0.1
0.2
0.3
0.4
0.5
Average Efficiency
Poly. (Average Efficiency)


N=20 K=18 (period 5000)
R^2 = 0.8052
0.665
0.655
0.645
0.635
0.625
0.615
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)


N=20 K=18 (average over 5000 periods)
R^2 = 0.93
0.665
0.655
0.645
0.635
0.625
0.615
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Average Efficiency
Poly. (Average Efficiency)


N=20 K=19 (period 5000)
R^2 = 0.9608
0.67
0.66
0.65
0.64
0.63
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
average efficiency
Poly. (average efficiency)


N=20 K=19 (average over 5000 periods)
R^2 = 0.9703
0.66
0.65
0.64
0.63
0.62
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
average efficiency
Poly. (average efficiency)

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