Cross-fertilization vs. Collaboration in Simulations of Open Innovation

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ABSTRACT
Evolutionary models allow us to approach innovation by the means of computer simulation with genetic algorithms. Open innovation can be considered in these models in different ways. A popular model by David Goldberg connects re-combinations of elements during evolutionary processes with the exchange of information in cross-fertilization activities. Another possibility is to model the collaboration of contributors with specific skills and experiences through sophisticated change operators that work systematically on improvements with respect to certain aspects of the innovation context. A simulation of this procedure on an instance of the permutation flow shop scheduling problem shows that the usage of these operators can indeed increase the performance of the solution generation, if certain constraints are kept in consideration.

General Terms
Algorithms, Management, Design, Economics.

Keywords
Open innovation and collaboration, evolutionary models, simulation, genetic algorithms.

1. INTRODUCTION
One and a half century after the publication of Darwin's "The Origin of Species", we continue to express the principles of evolution using the biological nomenclature of survival, genetics, generations and ecology. Nevertheless, the idea of a set of entities adapting over time under selective pressure from the outside is first of all just a formal concept without any specific field of application. It has been adopted by various different disciplines, including economy. The first concise treatments of evolution from the perspective of economic theory already date back to the nineteenth century [1], [2]. In the twentieth century Joseph Schumpeter connected innovation to evolutionary principles, describing it as a source of continuous change that is driven by the search for competitive advantage [3]. After several decades in which economics showed comparatively little interest in this approach, it regained popularity during the 1980ies [4], in many ways due to the seminal paper by Richard Nelson and Sidney Winter [5].

While the idea that change in economic systems is based on evolutionary principles sounds generally quite convincing, its specific application is not as easy as one might expect [6]. One of the major problems that also affects biological research is the determination of the actors in evolution [7]. Who exactly evolves? Genes? Individuals? Populations? Ecosystems? An evolution of genes cannot explain how genes came into existence in the first place; an evolution of individuals does not make sense, because they are replaced by others instead of being changed; an evolution of populations has objects of reference that constantly change their characteristics and are hard to pin down; and an evolution of ecosystems includes the environment that is supposed to be an external factor. Another problem concerns the change operations. How much variation is necessary from one generation to another? What kind of variations is most beneficial to the development? How can the variation of the mechanisms that create variation be included in the process? Evolutionary models give an explanation how current populations of individuals came into being, but they do not guarantee continuous improvement. Evolution can as well lead from a momentary advantage to extinction in the future.

The concept of evolutionary change can therefore easily be connected to narratives of success that explain how certain actors in economic systems gained an advantage over others. It is much more difficult to design an evolutionary model to support managerial decision making by predicting future development without the clear setting of a narrative. This is a common problem in the field of innovation management. In spite of the abundance of stories that are told about successful innovation, there is not really much to say that would support managers in their everyday decisions. Managers know that continuous change in products, processes and business structures is necessary to cope with the selective pressure exerted by the market, but they have incomplete information about how to induce and control this change. Even so, however, thinking in evolutionary terms can help managers to gain a better understanding of the different aspects that have to be considered in their decisions.

In many ways, evolutionary thinking provides the subtext of the current discussion about open innovation. According to Henry

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Chesbrough [8], modern businesses have to exchange information with external contributors in their innovation activities in order to cope with increased competition and scarce resources. Open innovation is, in this sense, a reaction to market exposure [9]. From an evolutionary perspective, the concept of open innovation can be said to interpret companies as individuals in a population under selective pressure from outside. They cannot only adapt to this pressure over time by isolated mutation, but also by the exchange with others. In biological terms, this would be called cross-fertilization. Open innovation thus represents a new reproductive strategy that is expected to produce a stronger generation of children than closed innovation. However, the details about how and between whom the reproduction should take place remains unclear.

This paper takes a closer look at the mechanisms of change in open innovation from a formal perspective. By considering evolution not as a biological metaphor, but an abstract formal concept, we are able to approach it by the means of information technology and use lessons learnt from the application of heuristic search algorithms to gain a better understanding of the specific challenges of managing open innovation.

The following sections are structured as follows. In section two, we introduce a formal concept of innovation based on evolutionary principles and discuss further insights into the impact of different change operators on the results of the process. In section three, we design a formal model of open innovation as an evolutionary process that turns the attention to the role of expert knowledge and collaboration in finding improvements. In section four, we use a simplistic innovation scenario to explore the potential of this model, which is further discussed in section five.

2. THEORETICAL BACKGROUND

The development of electronic data processing and the rise of modern information technology has been an important source of influence on the studies of evolution and their consideration in economics and other disciplines during the last decades. Digital computers are designed to execute a large number of logical operations in short time; they are therefore a very useful tool to simulate adaptive phenomena that are caused by the combination of many change routines.

It also turned out very quickly after the design of the first digital computers that it was possible to apply these simulations of evolutionary developments and similar procedures to solving optimization problems in complex search spaces (cf. [10]). For this purpose, the core elements of the evolutionary process were formalized in the concept of what is now known as genetic algorithms [11].

Figure 1 shows a rough sketch of the evolutionary process implemented in genetic algorithms (cf. [12]). The search starts on a set of possible alternatives to solve the problem. This set is called the initial population. In course of the search, the alternatives in the population repetitively go through changes which are usually carried out by simple mutations or re-combinations of the alternatives. As the genetic metaphor indicates, these operations are inspired by the study of biological reproduction. With a mutation, certain characteristics of the alternatives are modified at random; a re-combination puts together complementary parts of two (parent) alternatives in order to create a new one. The operations have no knowledge about quality. The evaluation of the changes in the population takes place separately in a subsequent step of the procedure, where the best alternatives are selected to form a new population while the others are eliminated. Since these changes are performed on alternatives which already possess positive characteristics, it is expected that the population will step by step develop into set of optimal alternatives, similar to the so-called survival of the fittest in nature.

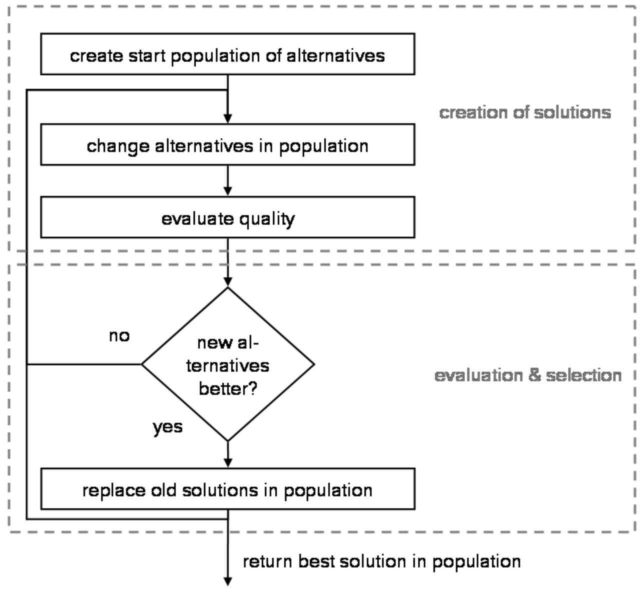

Figure 1. Evolutionary process in genetic algorithms

As a point of reference for evolutionary processes in general, genetic algorithms have been used to research how technical change becomes possible. According to David Goldberg, mutation and recombination in combination with the selective pressure from outside represent the fundamental activities in research and development [12], [13]. He argues that the combination of mutation and selection describes continuous improvement processes as they are addressed, for example in kaizen, which leads to a higher efficiency of processes that are already implemented. The combination of selection and re-combination leads to improvement by a new arrangement of the single elements that define a technical solution. This rather changes the effect of technology than its efficiency, which Goldberg calls cross-fertilization.

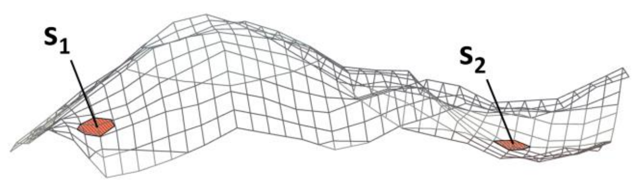

Figure 2. Illustration of landscape with neighborhoods

A formal approach to understand the differences between these two kinds of operators can be based on the concept of local neighborhood search. A neighborhood of an element ***s*** of the solution space is a subset of the solution space that contains elements that can be, in some way, easily reached from ***s***. This might be an area around ***s*** that you can access by a certain number of steps in a landscape (see figure 2). Mutation operators also provide a notion of proximity. They induce neighborhoods on the solution space covering all elements into which a solution ***s*** can be changed by one mutation. In combining arbitrary parts of two different solutions, re-combinations follow a different logic. The resulting solution may be far away from both its parents with respect to the topology induced by mutations (see figure 3). This allows the algorithm to get quickly into parts of the solution space which are difficult to reach when only mutation operators are applied. At the same time, however, it disrupts the structure of each of the original solutions to a much higher extent, which may destroy the improvement achieved by adaptation through repetitive mutation and selection before.

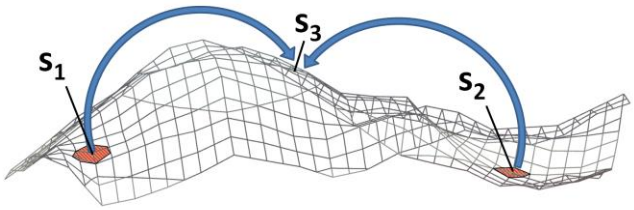

Figure 3. Illustration of possible effect of re-combination

Genetic algorithms accordingly show a poor performance if mutations or re-combinations are used exclusively [13]. The success of the concept relies on their interaction in reference to the distribution of optimal elements in the solution space. For some problems re-combinations must be applied more frequently than mutations; for others the opposite may be true. Another important factor for the performance of genetic algorithms is the size of the population (see also [14]). Various researchers have also looked into the possibilities to improve the performance of genetic algorithms by using more refined operators for changes. This includes two different types of operators [10]: on the one hand, operators remembering which solutions have previously been erased from the population and avoid choosing them again (mostly know as Tabu Search); on the other hand, so-called hill climbing operators which construct better solutions based on additional knowledge about the evaluation function. Such operators soften the separation of solution generation on the one side and evaluation and selection on the other side in the evolutionary design. Studies show, however, that they can significantly improve the performance of genetic algorithms and related concepts of heuristic search [e.g. 15, 19].

3. RESEARCH MODEL

Goldberg captures innovation processes in a very general model with relatively simple random change operators. One of the huge advantages of this model in comparison to other approaches to innovation is that it allows a discussion of innovation procedures in terms of operational performance without any further assumptions about the quality of the result or is utility for the company. Goldberg makes clear that innovation has to be managed for the simple reason of enabling the search to progress: in order to find good solutions, the combination of continuous improvement and cross-fertilization activities must take the given problem situation into account.

This corresponds with the idea of open innovation as broadcast search which allows contributions from everyone in disregard of their qualification and expertise [16]. The broadcast approach to open innovation assumes that sophisticated solutions will be submitted, but it does not make any assumptions about where these solutions come from. They may just as much have evolved from a random process as they may rely on professional training. The broadcast approach also takes little interest in the qualification and expertise within the company, claiming that the size of contributors from the outside can make up for any specific competence available inside [16]. In evolutionary terms this corresponds to the claim that cross-fertilization in big populations improves the quality of solutions.

The lead-user approach holds a different view on open innovation by assuming that the most valuable contributions are made by people with specific qualifications and expertise [17]. Open innovation is, in this sense, not focused on a blind expansion of the number and diversity of contributors. The added value of the so-called lead-users is based on specific sets of competencies they can add which are not available within the company. In contrast to broadcast search, the application of these competencies in not left to coincidence but carefully designed. The innovation process follows the pattern of a local search, as it would inside a company, but on a larger repertoire of change mechanisms. Lead-users, one could say, have a topological impact by expanding the neighborhoods of accessible solutions in specific directions. Speaking in evolutionary terms, the attention moves from the impact of the size of the population towards the application of different change operators. Including lead-users in the search is in this sense not very different from using larger varieties of tool-sets or methods for innovation.

At first sight, the lead-user approach may seem to have little to do with an evolutionary concept of innovation, because the external contributors are usually integrated into a rather analytic research and development process instead of a purely heuristic activity. It is therefore important to understand that contributions of the lead-users continue to have a different character than those that are made inside the company. This is illustrated by the phenomenon of sticky knowledge which indicates that the competences of the lead-users are not entirely transferable to internal experts [18]. Because of this "stickiness", the solution procedures of the participants in the solution process are essentially different. Neither one nor the other can exhaust the full potential of their collaboration in the creation of solutions.

This leads us to propose that collaborative forms of open innovation like the lead-user approach are also based on evolutionary principles. However, they rely on more sophisticated and goal-oriented change operators than re-combination for cross-fertilization.

In order to give an adequate account of all the facets of open innovation, Goldberg's evolutionary model therefore has to be expanded to include other kinds of operators. In addition to simple mutations and re-combinations, it is also necessary to consider changes in the solution space that are directed at certain explicit improvements. Different contributors to the process thereby have to be represented by different change procedures. An engineer, for example, can be expected to work on a higher technical efficiency of a machine, while a lead-user improves handling routines or infrastructure.

Since the objectives behind these improvements are not the same, they can, of course, have contradictory results. Better handling might reduce the efficiency of a machine and vice versa. This is a rather common phenomenon in multi-objective optimization and it seems justified to assume that any innovation activity can be considered as such. What remains to be shown is that change operators which provide improvements in different directions can indeed contribute to an overall better solution quality. We therefore put forward the following hypothesis:

H1 Operators working constructively on one-dimensional improvements in a multi-objective problem can increase the overall solution quality in an evolutionary search process.

In addition, we expect that open innovation initiatives that involve experts can outperform those that only work with the general public. In our research model, this expectation is expressed by the following hypothesis:

H2 The usage of one-dimensional constructive operators in a multi-objective problem can improve the performance of a heuristic search process in comparison to one that only applies mutation and re-combination operators.

The two hypotheses will now be tested in a simulation. For this purpose, we use a permutation problem which refers to a set of different items to be put in sequence. The sequence is evaluated with respect to certain targets such as minimum or maximum distances between items with similar attributes, batches of a certain number of similar items, one following the other, etc. For each target, an evaluation function is available that measures how well the target is met in the sequence. The results are accumulated in a weighed sum.

Permutation problems appear in a variety of scenarios, including the production of items in a flow shop where the target can refer to certain constraints of the machines that are used, or the composition of a musical tune, following a certain harmony and rhythm. Improvements for single objectives can be achieved, for example, when certain items are distributed evenly over the sequence or when certain distances between them may be enforced. Whether or not this change leads to an overall improvement of the solution remains unclear, because its effect with respect to other criteria cannot be predicted. One could say that each operator only represents a limited perspective on the innovation process. From this perspective, however, it will induce improvement of the solutions that random change operators would hardly be able to achieve.

4. SIMULATION AND FINDINGS

Our solution scenario is inspired by a common flow-shop scheduling task in a factory [19]. The solution space consists of a sequence of 256 items. These items carry attribute codes C1..C5, P1..P5P and Q1..Q4. Table 1 gives insight into the frequency in which these attributes appear among the items.

Table 2. Distribution of attributes in sample

No	Code	Amount
1	C1	53
2	C2	6
3	C3	72
4	C4	142
5	C5	70
6	P1	52
7	P2	18
8	P3	9
9	P4	16
10	P5	135
11	Q1	75
12	Q2	60
13	Q3	40
14	Q4	111

On these attributes, targets are defined according to Table 2. Note that each target can be met if no other target has to be considered, but all targets together can never be met at the same time. Any solution that is optimal for one item therefore has to be suboptimal for another.

Table 2. Targets on sequence

No	Code	Target
1	C2	Batch of 3 items in a row
2	C3	Batch of 2 items in a row
3	P2	Batch of 5 items in a row
4	P4	Batch of 2 items in a row
5	C4	Maximum 3 items out of 4
6	Q2	Maximum 3 items out of 6
7	Q4	Maximum 4 items out of 7
8	P1	Minimum 4 items out of 20
9	P5	Minimum 2 items out of 4
10	C5	Minimum 1 items out of 4
11	C1	Even distribution over sequence
12	C3	Even distribution over sequence
13	Q1	Even distribution over sequence
14	P4	Even distribution over sequence
15	P3	Even distribution over sequence

For each target, a constructive operator is defined that rearranges a randomly chosen part of the sequence such that the target is optimized. In addition, mutations and re-combinations are also defined as operators. These operators are used by a genetic algorithm on a population of 20 elements. The algorithm iterates the following procedure:

- On each single element of the population an arbitrary change operator is applied to create a new solution
- New and old solutions are merged in a set and evaluated
- The worse half of the set is deleted; the better half forms the new population for the subsequent iteration

The following table shows the results of the execution of the algorithm over 5 runs with 20.000 iterations. For comparison, the algorithm was also run five times using only re-combination and mutations. In 8 out of 10 runs, the final solution quality was already approximated by 95% after 15.000 iterations and the frequency of improvements was significantly reduced, leading to the assumption that improvements in further iterations would have been minimal.

Table 3. Result in different runs

Run	all operators	only simple operators
1	0,1529	0,4868
2	0,1209	0,5091
3	0,1416	0,4996
4	0,1287	0,3581
5	0,1411	0,4124
Avg	0,1370	0,4532

The results of the simulation runs using all operators are strongly superior to the results of the runs using only the simple operators, proving both H1 and H2. Further test runs with a higher number of iterations and with a larger population have confirmed these findings. A more detailed look, however, shows that the algorithm still benefitted from the simple operators, even if all operators were available. About 50% of the improvements achieved on solutions were caused by simple mutations or re-combinations. No re-combination, however, was able to create a best solution in the population.

5. CONCLUSIONS

A large number of case studies and discussions about best practices in the usage of specific tools and methods have given us a lot of insight into the phenomenon of open innovation during the last years (e.g. [20]). They have made clear that open innovation expands the possibilities of research and development in many different directions. In order to capture all of them in a general modelling approach, it is necessary to refer to a fundamental concept of change as it can be found in evolution. Although evolution is often referred to in economic discussions, the whole range of possibilities to apply the concept of adaptive change under selective pressure has so far not been exhausted. This is particularly evident for the application of different heuristic change operators.

Conventional research and development processes in a company are usually not considered to follow evolutionary principles, since they are bound to a clear systematic of consecutive steps for construction and decision-making. Open innovation, on the other hand, highlights the heuristic element in idea creation and its implementation in new processes, products and services: There is no deterministic way to predict how research and development will proceed, but instead a heterogeneous set of contributions which can lead to unexpected and surprising solutions. Broadcast methods in open innovation can be considered to form the antipode to conventional research and development inasmuch as they do not make any assumptions about competencies and experiences among the contributors to the solution. In this respect, the result of the innovation activities relies exclusively on the number of people who are included and the evaluation procedures for the selection of the results. As we have seen, this is compatible with the idea of cross-fertilization in evolutionary models. Open innovation, however, can take on many other shapes as well that consider specific capabilities, tools and methods for solution generation in different ways. Research and development are thus not only cross-fertilized by external input, but expanded by further forms of collaboration to connect the activities inside and outside of a company. This paper has looked into the question how these forms of collaboration can be arranged with an evolutionary model of change.

The concept of neighborhoods on the solution space makes it possible to address different search topologies induced by the operators that are applied to change the elements of a population. The research model developed in this paper interprets collaboration as an interaction between change operators which work intentionally on improvements of solutions in different directions. A simulation has shown that the application of these operators does not necessarily have to be fully synchronized and coordinated to yield better results. Quite in the contrary, their interaction might lead to overall improvement even if the single changes of the solutions contradict each other. This provides formal proof that open innovation and closed innovation do not have to be considered as two isolated antipodes to each other. There is instead a continuum of different levels of openness that leads from internal to external activities and allows many different combinations between both.

The findings of this paper contribute to scientific research in various ways. First, they give an example for a new formal approach that allows a better distinction of different settings and mechanisms in open innovation. This may prove to be helpful for developing a clear systematic to evaluate different forms of open innovation and their impact on the innovation process. Second, the findings of this paper show how the means of simulation can be applied to research on open innovation. The instance used here is still rather specific and so far hardly transferable to a general case, but the underlying concept can serve as a blueprint for further studies on a different scale. Third, the paper also holds implications for applied research on the organization of open innovation in practice. By considering open innovation as a heuristic search process according to the model used here, the insights that were gained on the usage of genetic algorithms can be used to look at the managerial decisions on open innovation from a new perspective.

The insights gained in this paper have an important limitation. It was shown that different and possibly contradicting change operations can nevertheless improve the performance of a heuristic search process. How the process actually will perform, however, depends on the specific setup, including the size of the population, the selection method used and the frequency in which the different operators are applied. These are the aspects of open innovation that decision makers have to look at when approaching it as a heuristic search process. In order to produce good results, all aspects of the search process have to correspond to the problem situation. This can also be interpreted as the setup of the search process inducing its own notion of the problem which may or may not fit to the real problem at hand. This is particularly important in situations where innovation represents a wicked problem that remains to a large extend intransparent. In this case, other criteria have to be applied to determine where a setup of open innovation as a heuristic search is considered successful or not.

Among other topics, further research will have to explore different formal representations of the results that innovation processes generate. While this may prove to be quite difficult in contexts where innovation is aimed at human interaction in services, other forms of innovation that rely more strongly on technical devices provide a very good basis for such a formalization. The application of such devices will, on the other hand, also lead to the notion of different change operators that can be compared with the methods drafted in this paper.

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