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The development of a Generic Innovation Network Simulation Platform

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I. Introduction

Innovation is increasingly recognized as requiring the convergence of many sources of knowledge and skill, usually linked in the form of a network. Today, few innovations can be assigned to a single specific technological field or even a specific firm (e.g. Klein, 1992). Accordingly, firms cannot expect to keep pace with the development of all relevant technologies without drawing on external knowledge sources. In this respect, today innovation networks are widely considered as an efficient mean of industrial organization of complex R&D processes. In most of the recent research in industrial economics and new innovation theory the increasing complexity of new knowledge, the accelerating pace of the creation of new knowledge and the shortening of industry life cycles are considered to be responsible for the rising importance of innovation networks.[1] Thus, mechanisms of learning and knowledge creation play the decisive role in the emergence of networks. In this light, networks are to be considered as a component of the emerging knowledge based society, in which knowledge is crucial for economic growth and competitiveness. In the knowledge based society not only the quantity of knowledge used is greater but also the mechanisms of knowledge creation and utilization are changing.

Although recent work in evolutionary economics and elsewhere has examined the role of innovation networks in technical change, but it has mainly been at the level of description, introducing for example the concept of *national* (Nelson, 1993) or *regional* (Cooke/Morgan, 1994) *innovation systems.* It has proved difficult to describe the complex dynamics of innovation networks using conventional methods of analysis (e.g. Pyka, 1999). In this presentation, we introduce a simulation approach developed by referring to a general theoretical model of innovation networks (Gilbert, 1999) and four empirically oriented conceptions of actual innovation networks. We consider innovation networks as evolving from the dynamic and contingent linkage of heterogeneous units each possessing different bundles of knowledge and skill.

[1] See e.g. Malerba, F. (1992) and Eliasson, G. (1995).

In order to study these co-evolutionary systems, the Self-Organizing Innovation Networks (SEIN) project[2] has assembled case studies to provide a practical cover set for systems of this type (see e.g. Weber/Paul, 1999, Saviotti/Pyka, 1999). The project has two primary foci: i) the empirical investigation of particular examples drawing on traditional techniques of social sciences and developing a typology of innovation networks (Ahrweiler, 1999) and ii) building on this, the development of a simulation platform for computational experiments in order to investigate the dynamics of technological collaborations and the emergence of persistent innovation networks.

To ensure commensurability between the empirically-oriented case studies and the theoretically-oriented simulation model, we are taking a two-pronged approach: the simulation platform supports the implementation of an abstract model of an innovation network (Gilbert, 1999), and, also constitutes the overall framework for the application of the specific case studies. This paper deals with the design of the platform to support the abstract model and its first application to the Biotechnology sector. For this purpose we start by motivating our approach from a methodological perspective by introducing simulation techniques as a tool for theory development. The basic components of the platform are then discussed and filled in by applying them to the Biotech case study. The paper concludes with some methodological considerations placing the analysis in a position between a purely deductive theoretical and a purely inductive empirical approach.

II. Methodological motivation

Since the experimentation structure drives the functionality of the simulation, the inputs and outputs of the simulation map directly to the premises and hypotheses under consideration. Since many of the premises this simulation platform will be asked to consider are programmatic (each experiment will consider actors who behave differently and constitute a different class structure and hierarchy, etc), part of the specification of those premises must be done in a programming language, rather than with a single, generic, parametrizable actor. Both that programmatic specification plus the usual initial conditions for any given run of the simulator constitute the inputs or premises. The outputs will typically be aggregate measures of the state of the simulation as it executes. These measures, like the individual models of the actors, themselves, will be abstracted to a large extent.

[2] The SEIN project is supported by the European Commission's Framework 4 Programme, contract SOEI-CT-98-1107. We acknowledge the assistance and advice of the other members of the project.

Since both the specification of the simulation (programmatic and initial conditions) and the measures are abstracted, we run the risk of inscription errors (creating our simulation in such a way that it is guaranteed to generate the results we seek). For this reason, close attention must be paid to causality in the simulation. An explicit separation is required between premises and hypotheses or between inputs and outputs. The mediator between these, the mechanism or dynamics, has to provide verifiable causal chains. For example, if, say, the actors in a simulation are defined to use a single broadcast channel of communication (meaning that all actors can listen in on any other actor's communications), the simulation will implicitly force interdependence between the causal chains of each of the actors. If a measure is then made of the connectivity or similarity between the internal state of the population of actor, the interdependence must be factored into the explanatory use of that measure.

A disciplined way to deal with the mediation between inputs and outputs of a simulation is to explicitly define observables for the model as measuring points on the various causal chains. Observables are defined as particular and specific elements in the simulation from which data can be taken. They are strategically placed so as to provide input to the calculations necessary to deduce the expected phenomena from the outputs of the simulation. This "data reduction" (which might more properly be called "data transformation") process is the foundation for simulation validation, where the simulation is compared to data taken from the real world, and scientific visualization, which transduces the outputs into a form where we can use our visual-spatial intuition to help us understand the dynamics of the mechanism we created. Data reduction then provides both the analytical and intuitive access to the dynamical system required for our, often ambiguous, criteria for emergent phenomena. With this in mind, a simulation must provide not only those observable points that support the hypotheses; but it must also provide a smattering of other observables in order to help us discover dynamics embedded in the simulation that we either mistakenly built in or that realize non-linearity. A methodological point to be made here is that distinguishing between the former and the latter type of embedded dynamic is often difficult; so an effort must be made from the beginning to distribute observables throughout the simulation that supports this distinction.

In order to provide a flexible enough framework for a reasonable distribution of observables in all the simulations our platform will support, we designed a simulator that tolerates the development of abstract, social network simulations as well as the implementation of specific, validateable, case studies. This allows our simulator to support as wide a range of functionality as possible with respect to the many ways simulation can be used to aid scientific study (Gross 2000).

III. Innovation networks

In an influential monograph, Gibbons et al. (1994) argued that knowledge production is in the process of changing from its 'traditional' locus in the ivory towers of academe to being much more closely connected with application contexts. Knowledge production in "Mode 2" is non-hierarchical and heterogeneously organised. The organisation of knowledge production is flexible, fluent and transitory:

> *Examples of this are numerous environmental and agricultural matters, diet and health problems, computerised databanks and privacy. Interactions between science and technology, on the one hand, and social issues on the other have intensified. The issues are essentially public ones, to be debated in hybrid fora in which there is no entrance ticket in terms of expertise* (Gibbons et al, 1994: 148).

The economic aspects of innovation have also received increasing attention. Based on the path-breaking work of Nelson and Winter (1982), the Schumpeterian research tradition has been merged with organisational and behavioural elements (especially Cyert and March 1963, Simon 1955) within an evolutionary framework of variation, selection and historical time, in order to capture the dynamics of innovation and their impact on growth, trade and technological change (cf. Dosi et al. 1988). One of the major motivations behind this work was a discontent with the lack of explanatory power of neo-classical economics in dealing with issues of technological change. In evolutionary economics, the technological element is captured in notions such as 'technological trajectories', i.e. distinct paths of technological development which dominate others and become selected. Several mechanisms have been identified which lead to the establishment of such trajectories. Prominent among these are the mental framework of scientists and engineers, labelled by Dosi (1982) as 'technological paradigms' (cf. Sahal 1985, Nelson 1987). Other important mechanisms are the persistence of established technological and economic structures or 'lock-ins' into certain technological pathways as a result of a reinforcement of minor comparative advantages or network externalities. In organisational and behavioural terms, evolutionary economics departs from the notion of profit-maximising agents and adopts the concept of 'routines' to describe decision-making processes.

While the earlier work of Nelson and Winter emphasises the market as the main selection environment of technologies, later contributions from a systems perspective pursue a wider approach, and focus on institutional elements as constraining the decision behaviour regarding innovations. Such 'systems of innovation' have been identified, especially at national (cf. Lundvall 1992, Nelson 1993), but also at regional levels (cf. Morgan 1997). Within this system context, learning processes among actors are regarded as being crucial, especially those between the users and suppliers and between competitors. From an evolutionary perspective, longer-term, paradigmatic changes in knowledge production are caused by changing patterns of selection in different social spheres: science and technology development, economic development, social changes, institutional factors, and mental frameworks.

The contributions of the sociological literature on innovation and industry dynamics, complements the work of evolutionary economics at the micro-level. Network analysis has revealed that new technological innovations are often a 'social construct' rather than or in addition to emanating from scientific and technological advances. Network relationships, which complement traditional markets and hierarchies have become more and more important for the production of knowledge. Systematic efforts using concepts such as 'actor networks' (Callon 1992) or 'socio-technical constituencies' (Molina 1993) have provided initial, if rather static analyses, but do not allow one to study and understand the dynamic behaviour of innovation networks.

Empirical research on the impact of policy measures, especially of regulation, has confirmed the important role played by the political realm in innovation processes. Recent work on policy networks has demonstrated the importance of close interactions between policy-makers and technology-makers for shaping the institutional and political environment of innovation processes (see for example in Marin and Mayntz 1991, Mayntz and Scharpf 1995). It recognises the need to look at actor constellations that shape the outcome of policy making processes, and at the interdependencies between institutional change and actor strategies.

In sum, the economic, sociological and policy literatures have begun to demonstrate that recent developments in knowledge production can usefully be conceptualised in terms of innovation networks. Nevertheless, they still leave several basic questions unanswered. There is no clear definition of what an innovation network is. Rather there are numerous specifications, each emphasising different aspects depending on the perspective of the proposer. Secondly, it is not clear whether there is a single phenomenon applicable to all spheres of innovation, or disparate processes with little or no commonality. Do the innovation networks in biotechnology have the same characteristics as those in telecommunications? Is it useful to treat the processes of knowledge production in the two sectors as similar? Thirdly, the literature is rather silent about the dynamics of innovation networks: how they arise, the growth processes they undergo, and the way they die or merge into other networks.

It is therefore necessary to begin to elaborate a theory of what constitutes an innovation network, together with its dynamics. In this paper we make a start by developing a simulation model of a 'generic' innovation network. The role of simulation in this context is not to create a facsimile of any particular innovation network that could be used for prediction, but to use simulation to assist in the exploration of the consequences of various assumptions and initial conditions, that is, to use simulation as a tool for the refinement of theory. The first part of this paper is concerned with the development of an abstract simulation model that could constitute a dynamic theory of innovation networks. In the second part of the paper, we apply this model to the particular case of biotechnology to show how the generic theory can be used to illuminate innovation in specific sectors.

The methodology we have adopted accords with Axelrod's (1997) description of the value of simulation:

> *Simulation is a third way of doing science. Like deduction, it starts with a set of explicit assumptions. But unlike deduction, it does not prove theorems. Instead a simulation generates data that can be analyzed inductively. Unlike typical induction, however, the simulated data comes from a rigorously specified set of rules rather than direct measurement of the real world. While induction can be used to find patterns in data, and deduction can be used to find consequences of assumptions, simulation modeling can be used to aid intuition* (Axelrod, 1997: 24-5)

IV. Description of the Model

The following description of the model is given in a very general form because the simulation platform can be applied to different contexts, in particular the four different case studies of the SEIN project, and can be used to emphasise different perspectives e.g. the economic or sociological perspective on the evolution of innovation networks. Later, the model is applied to the Biotech case in order to ground the abstract modelling concepts.

Actors

The starting point for our conceptualisation of an innovation network is the actors. These are mainly firms engaged in research and development (R&D). In addition, there are also political actors, venture capitalists, and universities and public research institutes that bridge the gap between applied and basic research.

Actors are represented as code that has the standard attributes of intelligent agents (Wooldridge and Jennings 1995):

- autonomy (operating without other agents having direct control of their actions and internal state)
- social ability (able to interact with other agents)
- reactivity (able to perceive their environment and respond to it)
- proactivity (able to take the initiative, engaging in goal-directed behaviour).

The actors in the simulation are able to learn from their own endeavors in research and from other actors with which they collaborate. The choice of whether to collaborate or to invest in research on their own, and the scale of R&D investment (and therefore its impact on their knowledge) is determined by the actors' *strategy*, which itself is an element of the actors' knowledge base.

Kenes

For the representation of actors we draw on a *genetic* description following the concept of *kenes* (Gilbert 1997). A kene is a collection of technological capabilities in different technological fields (1, 2, ... n) C_1, C_2, ..., C_n and is used as an approximation of the knowledge base of an actor. Each capability, C_1 to C_i, has a qualitative or quantitative value, one from a range of possibilities for that capability. The idea of a kene is illustrated in figure 1.

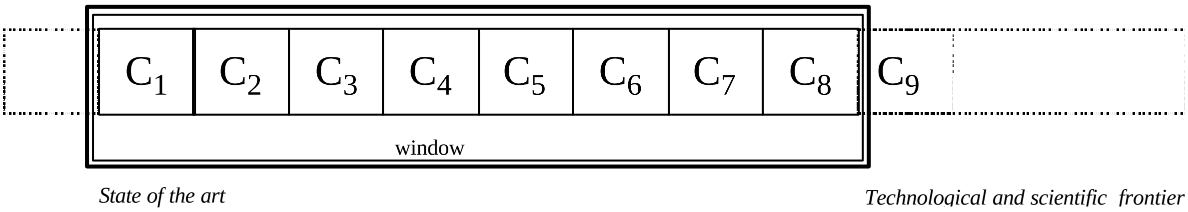

Fig. 1: A kene

A kene can grow in length and complexity thereby allowing the emergence of new knowledge fields. New technological capabilities can be added and old ones become obsolete. In this respect the kene is considered as a variable length window, shifting to the right as new capabilities are developed. Besides technological capabilities, an actor also acquires experiences (absorptive capacities[3], experience in networking[4] and in selecting a cooperation partner and so on) that can be summarized under the notion of competencies and that reflect the *knowledge history* of the actor. Actors also retain factual data about their past performance, number of former partnerships etc.

To summarize, actors are defined by their kenes, their competencies and their structural and behavioral attributes which determine their ability to observe, anticipate and design the product space. Accordingly, the actors in our model of innovation networks are heterogeneous because they differ in knowledge, experience, performance capacities, power, access to resources and in their intentions to design, shape, join and change networks.

Actors take advantage of their technological capabilities to produce artefacts. This is modeled by evaluating the kene to yield a list of attributes describing the characteristics of the potential outcome of the innovation process. Depending on the setting, the artefact might represent a new design, a new drug, new knowledge for which a patent application could be made, or a new discovery.

The Innovation Oracle

This *potential* innovation then serves as an input to an institution we label the *innovation oracle*. This is a 'black box' which evaluates and selects those artefacts that are to count as innovations. Fig. 2 illustrates the scheme.

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[3] Cohen/Levinthal (1989).

[4] See e.g. Pyka/Saviotti (2000).

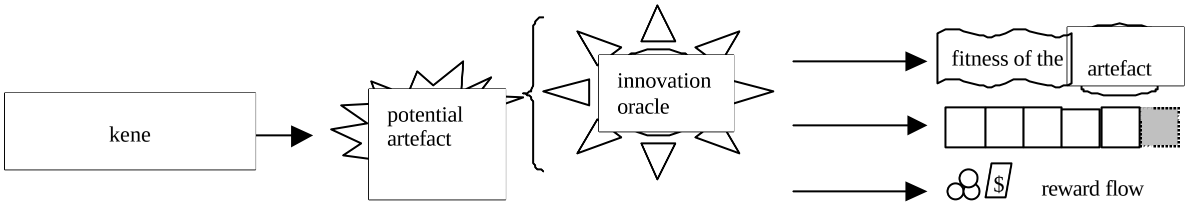

Fig. 2: From kenes to artefact

The oracle receives the potential innovation and generates three outputs: a value akin to a fitness measure about the success of the innovation; a report which proposes, in general terms, the type of additional knowledge that might be required to improve the innovation; and a reward that flows to the successful innovators. The oracle thus constitutes the selection environment for innovations. Its design will vary between case study settings, to reflect the determinants of whether innovations succeed. For example, a journal editor has the role of an innovation oracle in the scientific community, pronouncing on the novelty and significance of submissions; in the pharmaceutical market, regulators carry out some of the oracle role. With the help of the oracle's report, actors decide how to improve their knowledge base. There are two strategies available: actors can decide to go-it-alone, or they can decide to learn from external knowledge sources by initiating or joining an innovation network.

Research and Development

Actors are able to invest the rewards that they obtain from successful innovation (e.g. money from the sale of intellectual property, or prestige from the publication of successful inventions) into research and development. R&D can have two consequences: first, the values of particular capabilities can change (remaining within the range of possible values). Second, much more rarely and involving much greater investment, the actor can add a wholly new capability to its knowledge base by means of R&D.

Networks

An innovation network consists of at least two actors joined by links such as contracts and informal agreements. Participate in an innovation network allows actors to get access to the capabilities of other actors which are otherwise difficult or impossible to be simply obtain due to their substantial *local*[5] and *tacit*[6] components. However, choosing the cooperative strategy also means sharing one's own knowledge with other actors. They are likely to become competitors when it comes to the application of the knowledge generated within the network. Therefore, the actors need to evaluate carefully the likely advantages and disadvantages of participating an innovation network.

Ultimately, if the degree of integration, stability and inter-connection is sufficient, networks can come to resemble autonomous agents themselves.

To find a partner or an innovation network in which to participate, actors have to initiate a search. The search will use the actor's knowledge of the environment and on the dispositions and restrictions of each participating actor. The effort devoted to search will depend on the search costs the actors are willing to pay, a characteristic that differs substantially among the case studies. After having found a subset of potential partners which are in line with the actor's demands (e.g. "what capabilities am I looking for?", "what kind of reputation should the likely cooperation partner have?" etc.) the actor ranks the potential partners in the subset and tries to negotiate an agreement with the best one.

The actors' experiences in integrating external knowledge and their absorptive capacities are of crucial importance. These traits affect the effectiveness with which the actors can learn from the other actors in the network. Learning from network partners is achieved by combining kenes using techniques drawn from genetic programming. This is discussed in more detail in section V.

Case Study Specific Frameworks

The distribution of rewards from successful innovation is specified in the collaboration agreement (e.g. R&D/cooperation contracts dealing with distribution of income, intellectual property, knowledge flows etc.) and models the prevailing behavior in the sectors described in the case studies. The calculation of the value attached to each successful innovation is the job of the innovation oracle. This varies between case studies, but may be specified as a set of ordinary

[5] See Stiglitz (1987).
[6] See Polanyi (1967).

differential equations (or other analytical model) describing the general framework for competition, diffusion etc. in the sector.

Summary

Figure 3 summarizes the basic structure of the model.

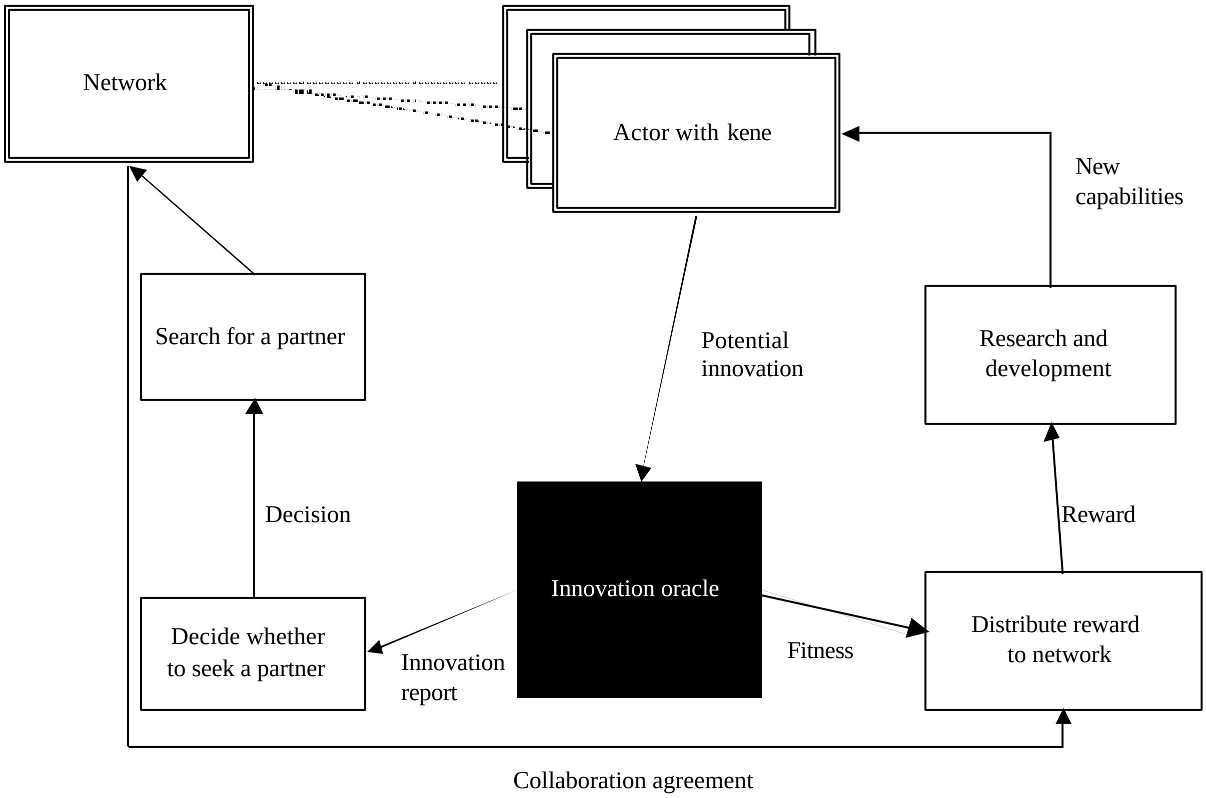

Figure 3: The structure of the model

The kenes of the agents are transformed in case study specific ways to generate potential innovations which are evaluated by an innovation oracle to assess whether they are true innovations ready to be exploited The actors obtain information from the oracle to support their decision about how to design their future R&D processes and whether they should join or initiate an innovation network. If they successfully locate a potential partner who is willing to cooperate, an innovation network emerges. This influences the learning processes, by modifying existing capabilities and creating new ones. When the innovation is successful, the 'rents' (rewards) are distributed according to the case study specific rewarding mechanism and the rules of the network concerning the distribution of intellectual property rights, new knowledge etc. The rewards can then be invested in research. An agent that fails to innovate successfully incurs the costs of research but receives no income and eventually 'dies', to be replaced by another agent with an initially random kene.

V. Implementation

The actors in the simulator are objects containing a property or attribute database as one of their instance variables. Within this property database the actor's kene is represented by an S-expression composed of operators and terminals. The operators are the set operators: union, intersection and set-difference. The terminators are instances of classes that represent capabilities. When evaluated, the S-expression yields a set of capability instances that constitutes the actor's 'potential innovation'.

The primary function of the executive in the simulator is to execute a genetic algorithm (GA) evolving these kenes. This is an elaboration of standard genetic programming (GP), with the oracle providing the fitness values (Koza, 1992).

During each cycle, the executive performs a GP crossover operation with the actor's kene and the kenes of the other actors in the network (if any). This operation consists of randomly selecting a subtree of the actor's kene, removing it and substituting a random subtree from one of the other actors in the network. This is then repeated for each of the actor's network partners.

The kene is also modified as a result of 'research and development'. The actor's strategy determines the relative proportions of the two types of R&D to be carried out:

1. a terminator is randomly selected and an instance from the same class is randomly substituted. This represents 'normal' R&D, providing the opportunity for incremental improvement through changes to the value of a capability. This kind of R&D has a relatively small cost to the actor's wealth (i.e. cumulated rewards).

2. A terminator is randomly selected and a randomly chosen instance from any class of capability is substituted. This represents the opportunity for more radical innovation (there is a chance that the instance may be from a capability not previously possessed by the actor or, indeed, by any actor in the population). This form of innovation is relatively expensive.

The innovation oracle receives the results of evaluating an actor's kene (a set of capability instances, representing the particular combination of skills and techniques required to create this potential innovation) and assesses it in a case study specific way. Typically, this will involve evaluating the set against all the other potential innovations the oracle has yet seen using a Hamming distance measure of similarity. If the potential innovation is distinct from previous innovations (and has other desirable attributes), it will be awarded a high fitness value. The oracle will calculate a reward for the innovation, which is typically proportional to the fitness value. It will also provide a 'report' on the innovation. This provides a hint to the actor about how the innovation could be improved (i.e. obtain a higher fitness value). This hint consists of a capability class. If the actor is able to provide an innovation including an instance of this class, it is likely (but not certain) to improve its fitness. The selection of 'hint' is again a case specific matter.

VI. The Biotech Case Study

In the following paragraphs we first outline recent developments in the biotechnology-based industries as an example par excellence of innovation networks and then illustrate the implementation of this case in the model.

VI.1 Innovation Networks in Biotechnology[7]

Although biotechnology can be considered as one of the oldest technologies used by mankind (yogurt making and beer brewing are illustrative examples), today biotechnology is at the forefront of the creation of a knowledge based society. With the discovery of recombinant DNA and monoclonal antibodies, the discipline of molecular biology was transformed into a seedbed of industrial applications. However, those industrial firms that were most likely to exploit the new technological opportunities offered by biotechnology did not at first have the knowledge base or absorptive capacities to take advantage of it. Their competencies were focused on the dominant disciplines such as organic chemistry or microbiology. Small firms, often those that had spun-off from universities, were the first to recognize the tremendous opportunities offered by biotechnology in sectors such as pharmaceuticals, agro-chemistry and environmental technologies. It was in these firms that the first industrial applications were developed. Additionally, in biotechnology, the frontier between basic and applied research is often blurred. Although the time between the discovery of new knowledge and its final embodiment in new products may be very long, the time between the creation of new knowledge and the funding of industrial research aimed at its application is in general very short.

[7] See Saviotti (1998).

Given this situation, it would be expected that the traditional actors, the so-called large diversified firms (LDFs), with their commitment to obsolete technologies, would either import the new knowledge or be replaced by science-based newcomers, the so-called dedicated biotechnology firms (DBFs). However, what has happened is that both types of firm continue to co-exist.[8] After a phase of sharing labor between both camps in the 80s, the LDFs began financing the R&D performed by the DBFs. This was the seed for the current networking structure in the Biotech based industries, which remains even in the 90s although almost all of the LDFs have developed their own competencies in biotechnology and have successfully re-oriented their own research departments to these new technologies. Today, DBFs are no longer considered as bridging institutions between new areas of basic research and their industrial application, but as extended R&D work-benches that provide LDFs with a broader orientation and more flexible research design. Innovation networks have thus become a persistent feature of industrial innovation in the biotechnology sector.

VI.2 The Implementation of the Case Study in the Model[9]

The most important *actors* in the Biotech case are large diversified firms (LDFs) and dedicated biotechnology firms (DBFs). Public research institutes and venture captalists are also important for this case study. The two populations of firms differ sharply in their original competencies and capabilities – their *kenes* in the terminology of the model. Whereas at the start the DBFs possess well developed competencies in biotechnology, the technological competencies of LDFs are completely oriented towards traditional technological approaches such as organic chemistry - competencies in the new field of biotechnology are almost entirely missing. However, technological competencies are not sufficient for the successful production and marketing of new goods. Economic competencies play a decisive and complementary role for legal approval, marketing, distribution etc. For the model, we assume that in the first place LDFs have well developed economic competencies whereas DBFs start with almost no economic competencies.

In addition and complementary to the technological competencies which constitute the basic knowledge needed for developing new technologies, the firms build up technological capabilities in the different strands within the biotechnology paradigm (e.g. gene-sequencing, combinatorial

[8] Grabowski and Vernon (1994)
[9] A detailed analytical model description of the Biotech simulation model is in Saviotti/Pyka (1999).

chemistry, bio-informatics etc.) oriented towards the introduction of an innovation based on these new technologies. These capabilities are created in timely and costly processes by investing resources into an R&D capital stock, the means for which become available either by earning money through sales or by receiving money within a research collaboration.

In the innovation process the competencies and capabilities of the firms are aggregated - the competencies thereby serving as a weight – and are transformed into an innovation probability. The innovation probabilities grow with positive but decreasing rates reflecting the limited technological opportunities of a specific technological trajectory – *there is and end to everything*, a relationship known in the history of technology as *Wolff's Law*.

In the platform model the innovation probability corresponds to the *potential innovation* and is matched every period with a Poisson-distributed random number which is the first part of the *innovation oracle* in the Biotech application. This particular distribution is chosen to reflect that innovation is considered to be a rare event. Here, a methodological advantage of simulation models compared to analytical models is revealed: there is almost no difference in an analytical optimization model between the modeled subject and the scientist's perspective. In contrast, numerical experiments allow for random distributions while the underlying statistical laws are hidden to the modeled subject. Drawing on this feature of simulation analysis allows one to come close to portraying true uncertainty, a decisive feature of innovation as emphasized in evolutionary economics.

Every time a new commodity passes the first part of the innovation oracle, the innovation is *evaluated by a market model* which basically has the structure of a heterogeneous multi-product oligopoly[10]. The quality of the innovation is compared with the qualities of already existing competitive goods and described with a two-dimensional vector containing the relative consumers' quality assessment as well as the price of the good. The competitive framework of the heterogeneous oligopoly finally decides on innovation rents which can be invested in the further exploitation of existing and the exploration of new technological trajectories. Accordingly, we find here a combination of the fitness value and the reward flow of the innovation which represents the second part of the innovation oracle within the Biotech application.

[10] A similar economic framework is used in Cantner/Pyka (1998).

To learn and build up their capabilities and competencies, firms can decide to access external knowledge and external funds in *innovation networks* supporting their innovative endeavors. An overall network probability which endogenously depends on the industry structure, the age of the industry life cycle etc. thereby determines the *potential cooperation space* by giving the maximum number of possible new cooperations or the number of existing cooperations which are to be terminated. As information on Biotech companies is widely spread and almost freely available on the internet –(published to attract venture capital) *search costs* do not play a role in this case study. So after firms have made their cooperation decision according to their specific requirements, they search for the best cooperation partner with reciprocal plans within the population of Biotech firms. By entering into bilateral relationships innovation networks emerge. These are responsible for considerable knowledge flows between the participating firms.

The knowledge flows within the innovation networks consist of the technological capabilities of the partners and are responsible for the *combination and reinforcement of their kenes*. However, as the *absorptive capacities* of the firms are not perfect, i.e. their capacity to integrate external know-how into their own knowledge stocks do not allow perfect imitation of tacit and local know-how, these knowledge flows are filtered, thereby also avoiding a technological assimilation of the involved firms. Nevertheless, the innovation probabilities of firms engaged in networking are positively affected in a twofold way by the external knowledge sources they can access: on the one hand, by joining a network with firms following a similar technological trajectory the pace of innovation is accelerated, on the other hand, by joining a network of technological heterogeneous firms, the potential qualitative impact of the innovative outcome is likewise higher because of cross-fertilization effects[11] between different technologies.

Depending on the different development stages of firms within the biotechnology-based industries different designs of collaborations are possible and these determine the *reward mechanism*. In order to reduce complexity we have chosen two basic collaborative designs that include almost all the contractual forms found in reality. The first design, ‘contractual R&D’, represents the relationships between established LDFs and start-up DBFs, as they were frequently found during the 80s: a LDF finances the R&D performed in a DBF because of a lack of its own competency in the biotechnology realm. By means of a contract, the large firm acquires not only all the intellectual

[11] See e.g. Kodama (1986) or Mokyr (1990).

property rights of the potential innovation, but also incrementally builds up own competencies. Start-up DBFs usually depend on these collaborative forms as they do not have their own funds necessary to undertake long lasting and expensive innovative endeavors. Although they have to give away the intellectual property rights of their innovation, they establish a positive reputation and also retain a certain amount of the money they receive from the LDF, which allows them to pursue their own independent technological developments. The second design, 'joint R&D', is found among more equal firms: two firms decide to combine their efforts in exploring and exploiting the technological opportunity space. The first firm successfully passing the innovation oracle is rewarded with the intellectual property rights. The other firm does not immediately gain from this innovation, but may profit later from other innovations generated from the additional capabilities provided through the collaboration.

VII. Conclusions

The increasing importance of innovation networks in technical change has been emphasised elsewhere, especially in the evolutionary economics literature. However, the processes by which networks are formed, and their role in innovation, is not yet well understood, partly because of the complexity of the dynamic processes involved and partly because the actors are heterogeneous and therefore hard to model using traditional techniques. We have shown in this paper how it is possible to approach these issues through the construction of an agent-based simulation model that allows one to specify, as hypotheses to be tested, the inter-relationships between new knowledge, knowledge transfer, selection from the market, and reward structures.

Our prime focus has been on the development of a conceptual basis and a theoretical perspective on the dynamics of innovation network formation. Although we have illustrated the model using a case study of Biotechnology, there remains a great deal yet to be done to test the model adequately. Such testing will involve two rather different approaches:

1. The behaviour of the abstract model itself needs to be explored, through a sensitivity analysis that will reveal the influence of the model structure. For example, we still need to determine under what circumstances the model generates collaborations between actors and therefore yields networks. Under some parameter settings it is possible for all actors to believe that collaborations would be undesirable, and that they would be more effective devoting their

resources to their own R&D. Alternatively, under other conditions it is possible for all actors to find the attractions of collaborations to be so strong that the result is a network that includes every actor in the model. Neither of these scenarios is unrealistic: there are sectors where networks are uncommon or do not exist and one of the other case studies being investigated by the SEIN project concerns a network that includes all the relevant actors within the UK. The model provides the opportunity for exploring the circumstances in which these and other scenarios are generated.

2. The SEIN project is collecting data about innovation networks in four sectors: Biotech, Mobile communications, Knowledge Intensive business Services and Combined Heat and Power. These represent four very different sectors and the characteristics of the networks in the sectors are correspondingly diverse. The model will be tested against data from these case studies. This will involve building a different innovation oracle for each.

Finally, it will be possible to draw policy conclusions about the consequences of fiscal and regulatory changes on the propensity for forming networks to encourage innovation in different sectors. The model can be sued to examine 'What if' questions to see, in a qualitative way, whether proposed policy changes are likely to have their desired effects.

References

Ahrweiler, P. (1999), Towards a General Description of Innovation Networks. Commonalities and Differences in the SEIN Case Studies, SEIN-Working Paper, #3, September 1999.

Axelrod, R. (1997) Advancing the art of simulation in the social sciences. In R. Conte, R. Hegselmann and P.Terna (eds.) *Simulating social phenomena*, pp. 21-40. Springer-Verlag, Berlin.

Callon, M. (1992): The Dynamics of Techno-economic Networks. In: R. Coombs, P. P. Saviotti and V. Walsh (eds.): *Technological Change and Company Strategy. Economic and sociological perspectives*. London: Academic Press, pp. 72-102.

Cantner, U., Pyka, A. (1998), Absorbing Technological Spillovers, Simulations in an Evolutionary Framework, *Industrial and Corporate Change*, Vol. 7.

Cohen W.M., Levinthal D. (1989), Innovation and Learning: The Two Faces of R&D, *The Economic Journal*, Vol. 99, 569-596.

Cooke, P., Morgan, K. (1994), The Creative Milieu: a Regional Perspective on Innovation, in: Dodgson, M., Rothwell, M. (eds.), The Handbook of Industrial Innovation, Edward, Elgar, Aldershot.

Cyert, R. M. and March, J. G. (1963). *A Behavioral Theory of the Firm*. Eaglewood Cliffs, NJ.: Prentice Hall

Dosi, G. (1982). Technological Paradigms and Technological Trajectories: A Suggested Interpretation of the Determinants and Directions of Technological Change. In: *Research Policy*, 11, pp.147-162.

Dosi, G., et al. (eds.) (1988): *Technical Change and Economic Theory*. London: Pinter.

Eliasson, G. (1995), General Purpose Technologies, Industrial Competence and Economic Growth – With special Emphasis on the Diffusion of Advanced Methods of Integrated Production, Working paper, Royal Institute of Technology, Stockholm.

Gibbons M., Limoges C., Nowotny H., Schwarztman S., Scott P., Trow M., (1994) *The new Production of Knowledge: The Dynamics of Science and Research in Contemporary Societies*, London, Sage Publications.

Gibbons, M., Limoges, C., Nowotny, H., Schwartzman, S., Scott, P., and Trow, M. (1994): *The New Production of Knowledge. The Dynamics of Science and Research in Contemporary Societies*. London: Sage.

Gilbert, N. (1997) 'A simulation of the structure of academic science' *Sociological Research Online* vol. 2(2), <http://www.socresonline.org.uk/socresonline/2/2/3.html.

Gilbert, N. (1999), First Draft of a Model of an Innovation Network, SEIN-Working Paper, June 1999.

Grabowski H., Vernon J. (1994), Innovation and Structural Change in Pharmaceuticals and Biotechnology, *Industrial and Corporate Change*, Vol. 3, 435-49.

Gross, L. J. (2000), Computer Systems and Models, Use of. To appear in: *Encyclopedia of Biodiversity*, Volume 1 (S. A. Levin, ed.) Academic Press.

Klein, B. (1992), The Role of Positive Sum Games in Economic Growth, in: Scherer, F., Perlman, M. (eds.), Entrepreneurship, Technological Innovation and Economic Growth, Studies in the Schumpeterian Tradition, University of Michigan Press, Ann Arbor, MA.

Kodama, F.(1986), Technology Fusion and the New R&D, *Harvard Business Review*, July-August, 1992, 70-78.

Koza, J. (1992) Genetic Programming. MIT Press, Cambridge, MA.

Lundvall, B. A. (ed.) (1992): *National Systems of Innovation. Towards as Theory of Innovation and Interactive Learning*. London: Pinter.

Malerba, F. (1992), The Organization of the Innovative Process, in: Rosenberg, N. et al.(eds.), *Technology and the Welfare of Nations*, Stanford University Press, CA.

Marin, B. and Mayntz, R. (eds.) (1991): *Policy Networks. Empirical Evidence and Theoretical Considerations*. Frankfurt a.M./Boulder, CO: Campus/Westview.

Mayntz, R. and Scharpf, F.W. (eds.) (1995): *Gesellschaftliche Selbstregelung und politische Steuerung*. Frankfurt a.M./Bolder/CO: Campus/Westview.

Mokyr, J. (1990), *The Lever of Riches*, Oxford University Press, New York.

Molina, A. (1993): In Search of Insights into the Generation of Techno-Economic Trends: Micro- and Macro-Constituencies in the Microprocessor Industry. In: *Research Policy*, 22, pp. 479-506.

Morgan, K. (1997): The Learning Region: Institutions, Innovation and Regional Renewal, In: *Regional Studies*, 31

Nelson, R.R. (1987): *Understanding Technological Change as an Evolutionary Process*. Amsterdam: North Holland.

Nelson, R.R. (ed.) (1993): *National Innovation Systems. A Comparative Analysis*. New York: Oxford University Press.

Nelson, R.R. and Winter, S.G. (1982): *An Evolutionary Theory of Economic Change*. Cambridge/MA: Harvard University Press.

Polanyi, M., (1962), *Personal Knowledge: Towards a Post-Critical Philosophy*, N.Y., Harper Torchbook.

Pyka, A. (1999), Innovation Networks in Economics. From the Incentive-based to the Knowledge-based Approaches, SEIN-Working Paper , #1, April 1999.

Pyka, A., Saviotti, P. (2000), Innovation Networks in the Biotechnology-Based Industries, SEIN-Working Paper #7.

Sahal, D. (1985): Technology Guide-Posts and Innovation Avenues. In: *Research Policy*, 14, pp. 61-82.

Saviotti, P. (1998), Industrial Structure and the Dynamics of Knowledge Generation in Biotechnology, in: Senker, J. (ed.), *Biotechnology and Competitive Advantage – Europe's Firms and the US Challenge*, Edward Elgar, Cheltenham.

Saviotti, P., Pyka, A. (1999), Conceptual Framework for a Simulation Model of Biotechnology Innovation Networks, SEIN-Working Paper #5, October 1999.

Simon, H. (1955): A Behavioral Model of Rational Choice. In: *Quarterly Journal of Economics*, 69, pp. 99-108.

Stiglitz, J.E. (1987), Learning to Learn, Localized Learning and Technological Progress, in: Dasgupta, P., Stoneman, P. (Hrsg.), *Economic Policy and Technological Performance*, Cambridge, Mass., Cambridge University Press.

Weber M., Paul S. (1999), Political Forces Shaping the Innovation and Diffusion of Technologies: an Overview, SEIN-Working Paper, #4, September 1999.

Wooldridge, M. and Jennings, N.R. (1995) Intelligent agents: theory and practice. *Knowledge Engineering Review*, 10: 115-152.