Chapter 2
Knowledge Networks: Structure and Dynamics

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2.1 Introduction

There has been recently an upsurge of interest in networks in a literature which belongs to many different disciplines, ranging from physics to biology to the social sciences. Interestingly enough, it seems that in spite of the wide differences between the entities constituting such networks, ranging from the interactions of biological molecules in cells to the Internet to citations (Barabasi et al., 1999, Barabasi, 2002; Barabasi and Bonabeau, 2003; Cohen, 2002; Watts and Strogatz, 1998), most such studies claim some kind of common intellectual framework rooted in complexity science. Yet the literature on networks does not provide any link between networks and other parts of the science of complexity which could be considered more fundamental. This contribution will proceed first to identify some possible connections between networks and other theories of complexity; second, to describe and analyse some networks of knowledge and innovation and to interpret their properties in terms of recent studies of networks; third, to formulate some generalizations about the dynamics of these networks and about their connection to the dynamics of variety and efficiency.

2.2 Networks and Complexity

Let us begin by asking the question 'why do we need complexity science?' and try and give it an answer mostly related to economic and social development. One of the most important tasks of a theory of economic development is to be able to explain some important stylized facts that we can observe in economic development. Some of the most important such stylized facts are listed as follows:

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(i) Economic systems do not become more random, or disordered, during their process of development.

(ii) Economic development is characterized by qualitative change, since the new entities emerging during its course are not comparable to previously existing ones.

(iii) The variety/diversity of the economic system rises during the course of economic development.

(iv) Order, or structure, emerges from the process of economic development. Changes in structure occur infrequently and are followed by long periods of more incremental variations.

As a consequence of these stylized facts, the composition, defined as the list of entities and processes required to describe the economic system, changes in the course of time. The important implication of all of this is that not all theories would predict this type of development. For example, the growing variety of the economic system could be expected to lead to a growing disorder or randomness (see for example Georgescu-Roegen, 1971). Amongst the theories of complexity, the one formulated by Prigogine (see for example Nicolis and Prigogine, 1989) has the great merit of providing a potential explanation for the growing order and for the growing variety of the economic system. Let us start by defining structure as given by the components of a system and by their interactions. We can observe here that the interactions provide constraint and reduce the number of degrees of freedom of the system with respect to those of its isolated components. It is precisely this constraint that creates order. The most important explananda in our economic system are (i) the emergence of order during the evolution of the system and (ii) the discontinuous transitions that the system seems to undergo during its evolution.

Prigogine introduced some fundamental concepts and distinctions, which are very useful in this sense. An important distinction needs to be introduced between closed and open systems. The former are closed because they do not exchange anything (matter, energy etc.) with their environment. Only closed systems can achieve an equilibrium, which corresponds to the maximum possible disorder or randomness of the components of the system, that is, to the contrary of the order we observe in economic development. Open systems exchange matter, energy, information etc. with their environment. The rates of flow through the boundaries of the system measure the distance of such system from equilibrium: the more intense such flows, the more the system moves away from equilibrium. The interesting behaviour of these systems only emerges when they are far enough away from equilibrium. In these conditions, structure may emerge first and transitions between different types of structure can occur subsequently. Transitions occur when the system, as a consequence of its previous development, becomes unstable and undergoes a transition to a different configuration. According to Prigogine, instability arises in the form of *fluctuations* in some system variables. When fluctuations become sufficiently intense they induce *bifurcations*, or transitions to different configurations of the system, which not are only different from pre-transition ones but can also be in higher numbers. As a consequence of bifurcations, the number of possible states of

the system can increase, thus providing an in-principle justification for the growing variety of the economic system.

Thus, Prigogine's theory gives a potential explanation to (i) the emergence of structure, (ii) the presence of transitions between distinguishable states of the system and (iii) the growth in the number of possible system states after the transition. Prigogine's theory provides a potential explanation for the stylized facts listed above. Incidentally, let us note that some very similar stylized facts apply to biological development. Prigogine's ideas provide an underlying theoretical framework for both biological and economic development. Of course, the existence of this underlying theoretical framework does not mean that exactly the same type of explanation will apply to biological and economic phenomena. Complexity theory is expected to be applicable to many different types of systems at a high level of generality. The complete analysis of each system involves such a general level and a more specific one requiring the use of concepts and variables specific to the system itself. Thus, the actual dynamics of biological and of economic systems cannot be expected to be identical even if at a high level of generality they share the non-equilibrium nature of evolution and the possibility of bifurcations.

What relationship can we expect to exist between Prigogine's theory of complexity and the existence of networks? First, networks are composed of nodes/vertices and of links/edges. The nodes are the components of the socio-economic systems and the links are their interactions. Thus, networks are the structure of socio-economic systems. Following the previous considerations, we can expect (i) networks to emerge away from equilibrium and (ii) transitions between different types of networks to occur, as the relevant system becomes unstable and undergoes a bifurcation.

We can imagine the development of human networks to have begun as a consequence of the most fundamental aspect of human behaviour, adaptation to the external environment (Ext.Env). From very early on, it must have turned out that collective adaptation was superior to individual adaptation. However, collective adaptation involved coordination of individuals' actions, resulting in a fall in the number of degrees of freedom that would otherwise have been available to individuals. The constraints existing in the communities that adapted collectively occurred in the form of *rules* (Dopfer, 2004) which limited and streamlined people's behaviour. Furthermore, coordination involved at its roots communication. Thus, the earliest systems of rules that could provide coordination must have been language and law. Such constraints on individual behaviour shaped inter-individual interactions and shaped the earliest networks.

On the basis of the previous considerations on Prigogine's theory of complexity, we expect the evolution of a system, represented by a network, to occur by means of a combination of the gradual adjustments of the system to its Ext.Env, combined with inter-system transitions, induced by fluctuations in the previous system configuration. It is to be pointed out that we can expect fluctuations to arise endogenously within the system as a result of its previous evolution. Fluctuations induce bifurcations, leading to discontinuous changes, giving rise to the emergence of new structures/networks. The emergence of new structures/networks occurs by

the creation of new boundaries and of new subsets of the system under consideration, with the possible disappearance of older subsets. In network terms, this amounts to the creation of new nodes and links and to disappearance of older ones.

In this context, fluctuations take an interesting meaning. Instability within an existing structure/network is likely to arise as a consequence of the instability of some existing links. This instability can be interpreted as a departure from dominant rules, which in turn can allow the exploration of new subsets of Ext.Env and the creation of innovations. This would be compatible with observations which imply that historically innovations have tended to arise more frequently in societies which were freer and less bound by tradition (see for example Landes, 1998).

According to stylized fact (iii) stated above, the variety of the economic system increases during the process of economic development. In terms of networks this could imply that the number of networks within the system increases. Another important feature of network dynamics is the evolution of their connectivity. In fact the variety of an economic system at best measures the number of its nodes but does not say anything about its links, which are an important part of its structure. Therefore, connectivity is an important part of network dynamics. We can expect innovations to be introduced by entrepreneurs in a rule-poor environment, which provides the required freedom and the scope for fluctuations. Not all fluctuations are successful. At any time most of them are likely to be selected out. Precisely for this reason, a society which is able to create more fluctuations will have a greater chance of having successful ones. However, if the innovation is successful we can expect it to be widely imitated and to diffuse gradually in society. In order to acquire its 'economic weight', an innovation also requires the co-evolution of appropriate institutions (Nelson, 1994). The creation of complementary technologies and of appropriate institutions leads to the formation of new links, thus raising the connectivity of the system. For example, the creation of a regulatory institution can be expected to lead to interactions with the firms and the other organizations responsible for the production and use of the new technology. These interactions may be impersonal and simply provide constraint, as it would happen in the case of standard-creating institutions, or be more localized and directed, as in the case of a firm producing complementary inputs to the innovation and technology concerned. Examples of these situations for automobile could be (i) the ministries responsible for issuing driving permits or driving rules and (ii) the firms producing and distributing tyres or petrol (Saviotti, 2005). In all these cases, the general meaning of links is that they reduce the number of degrees of freedom of each node and provide constraint. The behaviour of the nodes then becomes more highly correlated. This progressive increase in connectivity as an innovation and the relative technology mature on the one hand increases the potential market size of the new technology by improving the technology with respect to its initial form but, on the other hand, makes the new technology progressively more rigid, even if more coherent. In this way, an increasing connectivity allows a technology to acquire its full 'economic weight' but contributes to the process, whereby diminishing returns gradually take over and slow down the rate of improvement of maturing technologies.

Network dynamics at the industry/technology level can be expected to be characterized by low connectivity during the emergence phase and by growing connectivity as the sector matures. At the aggregate level of the whole economic system, increasing diversity/variety means an increasing number of nodes. However, this increase is likely to be unevenly distributed in time and space. The creation of new nodes cannot be expected to be followed immediately by the creation of new links. The emergence of important innovations can be expected to lower connectivity while the subsequent process of diffusion can be expected to raise connectivity. Thus, aggregate connectivity cannot be expected to grow at all times, but it could easily oscillate around a given value.

We can then expect some relationships to exist between the evolution of variety and that of networks. Variety grows by the creation of new economic species (new products, services etc.):

- First, we can expect the creation of new economic species to lead to a growing number of distinguishable networks.
- Second, we can expect the phase of emergence of new economic species to occur in an institutionally poor environment characterized by a low connectivity, but we can also expect the subsequent phases of diffusion and of maturation of new technologies to lead to a growing connectivity.

It has been recently discovered that a large class of networks possess some common properties for which they are called scale-free (Barabasi and Reka, 1999; Barabasi et al., 1999; Barabasi, 2002; Barabasi and Bonabeau, 2003; Reka et al., 2000; Reka and Barabasi, 2002). In particular, these networks have a very asymmetrical distribution of links around nodes: few nodes have many links and many nodes have few links. This distribution is very different from that predicted for previously studied networks, called exponential networks, which had a much more egalitarian distribution of links around nodes. Scale-free networks have a power law distribution while exponential networks have a Poisson distribution of links around nodes. As a consequence, scale-free networks have the interesting property of being very resistant to random attack: almost 80% of the links can be cut before a scale-free network is destroyed, while the corresponding percentage for an exponential network is less than 20%. However, a targeted attack selectively cutting links around the most central nodes (hubs) destroys the network by cutting less than 20% of the links.

Two conditions are required in order for scale-free networks to exist:

 (i) growth – the number of nodes must grow;
 (ii) preferential attachment – new links tend to be formed more easily with already linked nodes.

These conditions are often present in socio-economic networks. In general, the observed growth in variety of a number of economic species (technologies etc.) can be expected to lead to a growing number of nodes. Thus, growing variety could supply one of the two conditions required for the existence of scale-free networks. In

socio-economic networks, the second condition – preferential attachment – depends on sources of increasing returns to adoption. Examples of these sources are reputational structure and various types of resources. Let us take the example of an alliance between an incumbent large diversified firm (LDF) and a start-up. In its choice of partner the start-up is likely to favour the LDF with the best reputation. If the alliance leads to a further enhancement of the LDF's reputation, other start-ups will continue to favour it with respect to other LDFs. Moreover, if a growing number of alliances raise the resource base of incumbent LDFs, those already having a greater number of alliances will be better able to form further ones than other LDFs. Thus, conditions (i) and (ii) can be often found in socio-economic networks. The presence of these two conditions leads to a higher probability of creation of scale-free networks than to other types of networks, or to a higher relative rate of *variation* for this type of networks. This condition is at best necessary, but not sufficient, to justify a high concentration of scale-free networks. However, one of the most important findings about this type of networks is their resistance to attack. If we interpret attack as selection, scale-free networks are likely to have a high rate of variation and a low rate of selection whenever conditions (i) and (ii) are satisfied. On the other hand, since conditions (i) and (ii) are often present in socio-economic networks, we can expect the scale-free geometry to be quite common in this type of network.

These network properties are obviously interesting and highly relevant for socio-economic networks. However, although research in scale-free networks has concentrated on the distribution of links around nodes, other related network properties are of great importance. For example, the existence of scale-free networks implies an uneven distribution of the degree of centrality of nodes. Few nodes are highly central while others have a low centrality. Furthermore, the distribution of centrality is likely to change dynamically, for example with the distribution becoming at times more skewed or more even, the relative centrality of some nodes falling and that of others rising. Another property whose role has already been discussed is connectivity. We have already seen how we can expect connectivity to rise or to fall during the evolution of networks. The meaning of this property will be discussed in greater detail in the next section.

2.3 Examples of Knowledge Networks

In what follows three examples of knowledge-related networks will be discussed:

  (i) The network of knowledge itself, which will be presented only conceptually but which will provide a good basis for the subsequent discussion.
 (ii) The network representing the knowledge base of firms.
(iii) Innovation networks (INs) in biotechnology.

2.3.1 Knowledge as a Network

Two very important properties of knowledge are (Saviotti, 2004)

  (i) Knowledge is a correlational structure.
 (ii) Knowledge is a retrieval/interpretative structure.

According to property (i) knowledge establishes correlations between different concepts and variables (see also Loasby, 2001). It is therefore possible to represent knowledge as a network whose nodes are concepts or variables and whose links are given by the joint utilization of the concepts or variables. In this representation, we would attain a complete knowledge of our Ext.Env if we had all the nodes corresponding to all the concepts and/or variables of our Ext.Env and if the corresponding network was fully connected. However, if we examine the way knowledge develops we can realize that we are very far from complete knowledge. As the exploration of our Ext.Env proceeds, we detect new observables and create appropriate variables. This is done on a *local* basis, that is, starting from a casual observation or from the solution of a practical problem (see also Popper, 1972). The subsequent evolution of different fields of knowledge gives rise to disconnected networks. Let us take an example.

In the past astronomy and medicine developed in completely separate ways. There was no awareness that the entities to which the problems could be reduced in the two fields had anything in common. Thus, astronomy proceeded by identifying observables (the sun, the earth, planets, stars etc.) and constructed models of the movements of these entities. Medicine on the other hand proceeded by identifying organs and by trying to explain the behaviour of the whole body by means of its organs. The awareness that organs were constituted by cells, cells by molecules and molecules by protons, electrons and neutrons took centuries to come. In other words, the networks of knowledge of astronomy and medicine were for a very long time separate, and it was not realized that they could in principle be connected. The awareness of the potential connectedness of these two and of other networks of knowledge came only during the nineteenth century and gave rise to the so-called Laplacian dream (Mirowski, 1989). One could say that the research programme of molecular biology aims at connecting the networks of biology and physics. However, and in spite of the considerable successes achieved in this direction in the last 30 years, we are still very far from having identified all the possible nodes and links. Thus, we can conclude that, although the final objective of knowledge is to construct a complete network, containing all the possible variables of our Ext.Env and all the possible connections linking these variables, the present state of our knowledge is very far from that.

Some observations can help in understanding the present state of our knowledge network. First, new observables are continuously discovered, although at a different speed in different disciplines. Some disciplines (e.g. chemistry) are closer to maturity and generate few new observables, while others (e.g. biology) keep generating new observables and variables. Second, the rate of creation of new nodes by the

discovery of new observables and variables precedes in general the creation of links between the corresponding variables. In many cases we can expect the construction of links to be a much slower process than the creation of new nodes. When, as a result of new discoveries, new nodes are introduced in our network of knowledge we can expect connectivity to fall. As links are established with the newly created nodes, the connectivity of the system can start rising again. We can reinforce here some trends we had already seen at a more general level:

   (i) The emergence of novelty tends to create new but poorly connected nodes, thus temporarily reducing the connectivity of the system.
  (ii) The subsequent diffusion of the innovations establishes new links and raises again the connectivity of the system.
 (iii) As a result of (i) and (ii), the connectivity of the system is likely to fluctuate around a given value.

   It is important to realize here the role that connectivity can play in the dynamics of socio-economic networks. Connectivity is generally measured by the density of links per node in a network. Since in knowledge networks links represent the existence of correlations between nodes/variables, in a high-connectivity knowledge network variables are highly correlated. In turn, the existence of correlations leads to a high probability of predicting the values of some variables from those of other correlated variables. On the whole a high-connectivity knowledge network leads to a high probability of predicting the behaviour of some parts of the network starting from the knowledge of other parts. When our knowledge network is used to modify a subset S of Ext.Env, a higher probability of predicting some parts of the knowledge network leads to lower costs of modifying a subset S(Ext.Env) (Saviotti, 2004). Thus, connectivity is a relevant property of a knowledge network, both in a cognitive and in a technological sense.

   The dynamic representation of knowledge used in this contribution (but see Saviotti, 2004 for greater details) is compatible with Kuhn's (1962) analysis of the evolution of science. New observables and variables are likely to be created when new paradigms emerge. In this early phase, we can expect new variables to be poorly connected to those existing in the previous network of knowledge. Thus, the emergence, or revolutionary, phase of a new paradigm is likely to be accompanied by a falling connectivity of the network of knowledge. On the other hand, we can expect the subsequent phase of normal science to be characterized by a growing number of links, and thus by a growing network connectivity.

   In a broader sense, the representation of knowledge as a correlational and as retrieval/interpretative structure is compatible with the idea of knowledge as an organized structure, to which both Kuhn's and Lakatos' theories belong (Chalmers, 1980). In particular, the representation of knowledge described in this contribution is compatible with some recent structuralist theories of science (Balzer et al., 1987; Franck et al., 1999) according to which the collection of all empirical science forms a theoretical *holon*, composed of constellations of elementary theories, theories that would be *connected* by inter-theoretical links of different types, such as equivalence, specialization, connection.

2.3.2 The Knowledge Base of Firms and Organizations

We can define the knowledge base of a firm or organization as the collective knowledge that can be used to achieve the firm's productive objectives. The term collective is due to the fact that the process of knowledge creation in the firm is based on division of labour and on coordination. Many individuals, departments, subsidiaries etc. of the firm contribute to the creation of new knowledge, each carrying out a small subset of the whole process. The production of the resultant knowledge necessarily involves the coordination of all these activities. Clearly the organizational structure of a firm can be expected to have an impact on the process of knowledge creation.
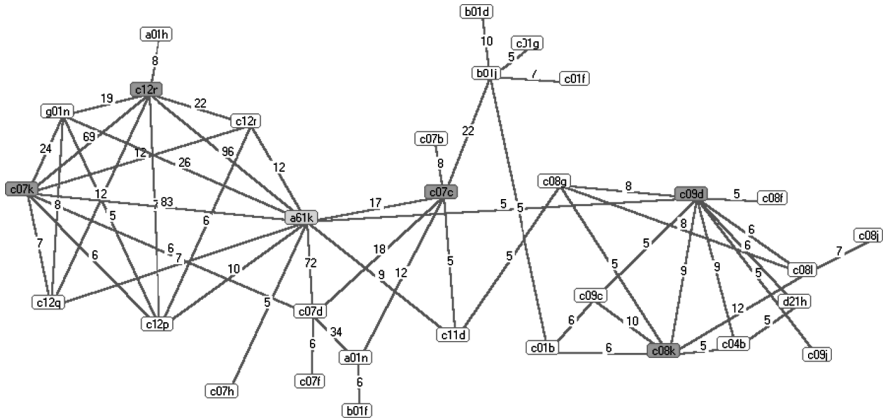
The study of firms' (and organizations') KBs is a very important component of the creation of an economics of knowledge. In this section, two different methods to map the KB and to measure its properties will be described. In both cases we start by identifying some basic units of knowledge. In principle, we could refer to the considerations of Sect. 3.1 and attempt to find all the variables corresponding to a given piece of knowledge. This is generally impossible and we use instead more aggregate units of knowledge, such as the technological classes contained in patents or the themes contained in patents or publications. The representation of the KB that we obtain by examining, for example, the patents of a firm is a network in which the nodes are constituted by our units of knowledge and the links by the interactions of the units of knowledge. In the work described here the interactions are measured by the co-occurrence of the units of knowledge in the patents or in the other sources of information that we are using.

The two methods we use to study firms' KBs are different in that they refer to different levels of aggregation. The first method, *lexicographic analysis* (*LA*), detects the units of knowledge in the texts that we use as sources of information. LA can detect in the text of patents short phrases corresponding to technological themes, or alternatively the technological classes contained in the patent. The links of these units are determined by their frequency of co-occurrence in the patents used. This provides us with a graphic representation of the network of knowledge constituting the KB at a given time. Repeating the study at different times we can map the evolution of the KB and relate it to changes in firm strategy, firm organization etc. (see Saviotti et al., 2003, 2005). In other words, LA allows us to represent the 'brain' of the firm.

The second method we use starts by constructing a matrix of co-occurrences of technological classes and provides us with a more aggregate representation of the KB. In particular, it allows us to measure some of the properties of the KB, such as its coherence, specialization, differentiation and similarity. On the basis of these measures, it is possible to show that the KB of a firm is a determinant of the firm's performance (Nesta and Saviotti, 2005). These two methods are complementary. LA provides us with a more disaggregate representation, by means of which we can enter the firm's KB, while the method based on co-occurrence matrices gives us measures of the resultant properties of each KB. The graphic representation shown here (Figs. 2.1, 2.2, 2.3, 2.4 and 2.5) was obtained by means of LA.

Figures 2.1 and 2.2 represent the KB of Hoechst for the periods (1993–1995) and (1996–1998). Figures 2.3 and 2.4 represent the KB of Rhône Poulenc for the

Fig. 2.1 Diagram for period 2 (1993–1995) of the co-occurrences between the main IPC classes of Hoechst (the most central classes are represented in dark grey)

periods (1993–1995) and (1996–1998). Figure 2.5 represents the KB of Aventis, the firm created by the merger of Hoechst and Rhône Poulenc. We can immediately notice some properties of this KB network:

- The distribution of the frequencies and intensities/strengths of links around nodes is highly heterogeneous. Few nodes have many links and other nodes have very few links. Also, some nodes have very strong links while others have very weak ones.
- In the KBs of both Hoechst and Rhône Poulenc we can see two parts which have a high internal density of links while being very lightly connected to each other.

Fig. 2.2 The KB of Hoechst for period 3 (1996–1998) as represented by the co-occurrences between the main IPC classes of its patents (the most central classes are represented in dark grey)
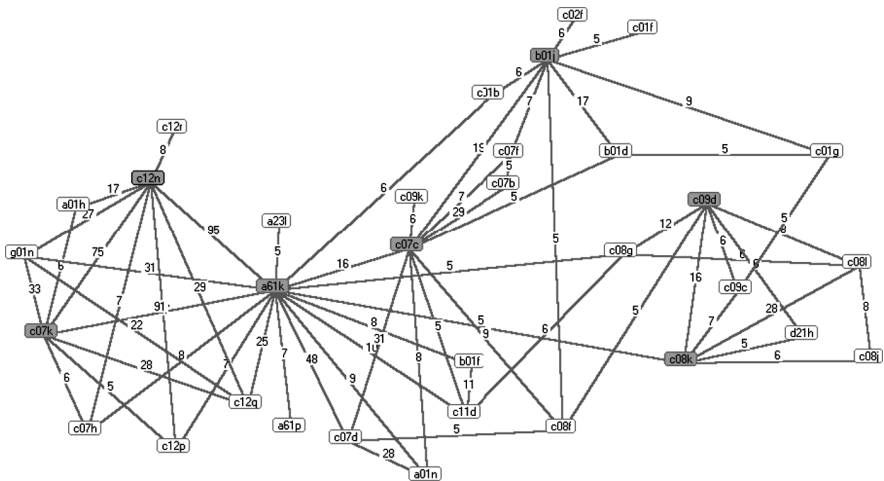
Fig. 2.3 The KB of Rhône Poulenc for period 2 (1993–1995) as represented by the co-occurrences between the main IPC classes of its patents (the most central classes are represented in dark grey)

Each of the two separate subsets of the KB of Hoechst and Rhône Poulenc corresponds to a different type of knowledge, chemistry and biology, respectively. Taking into account that during the period studied the two firms were attempting to move away from chemistry and towards life sciences, the two subsets correspond to the past and to the intended future of the firm, respectively. In other words, Figs. 2.1, 2.2, 2.3 and 2.4 represent the changes in the KB of both firms following from their strategic reorientation.

- Figure 2.5, representing the KB of Aventis after the merger, no longer shows the separation into two distinguishable subsets, corresponding to chemistry and

Fig. 2.4 The KB of Rhône Poulenc for period 3 (1996–1998) as represented by the co-occurrences between the main IPC classes in its patents
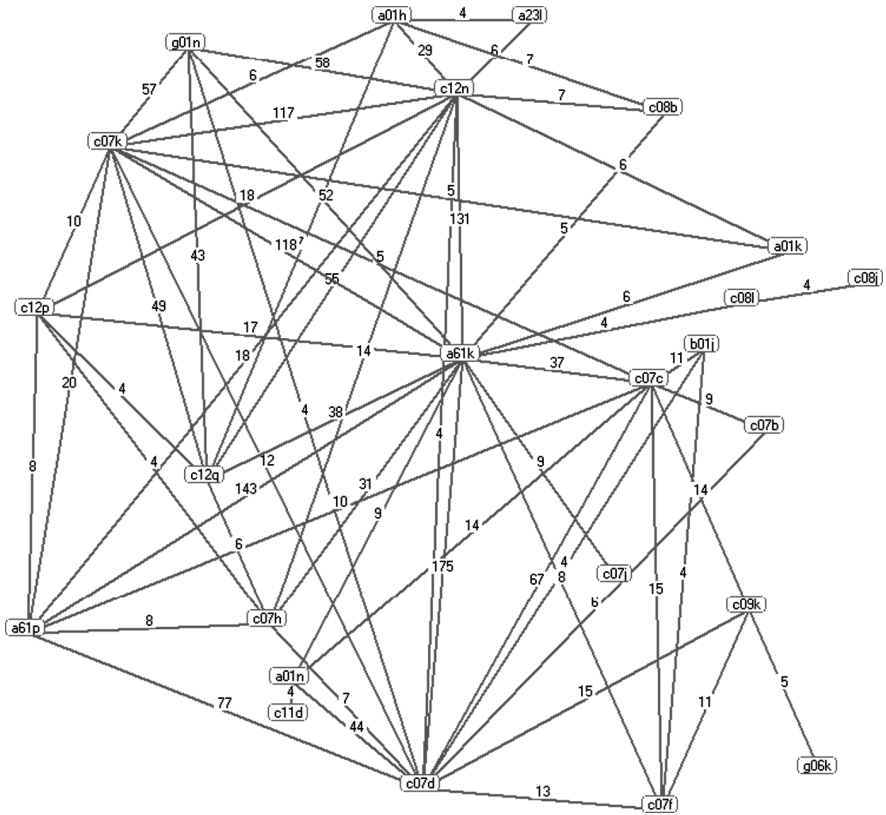
Fig. 2.5 The KB of Aventis after the merger, as represented by the co-occurrences of the technological classes in the patents of Aventis

to life sciences. The whole KB seems to be better connected, realizing a more complete integration of old and new knowledge. This better integration is confirmed by a measure of the number of links per node, which can be considered an approximate measure of network density and which is considerably higher for Aventis after the merger with respect to both Hoechst and Rhône Poulenc before the merger (Table 2.1). Furthermore, the distribution of links around nodes is highly asymmetrical.

Table 2.1 Number of nodes, links and links per node in the above representation of the KB of Hoechst, Rhône Poulenc and Aventis

	Hoechst		Rhône Poulenc		Aventis
	P2 (1993–1995)	P3 (1996–1998)	P2 (1993–1995)	P3 (1996–1998)	2002
Nodes (N)	33	22	31	32	24
Links (L)	55	36	46	54	73
L/N	1.67	1.64	1.48	1.69	3.04

2.3.3 Innovation Networks

Another type of knowledge-related network that we studied is that of INs in biotechnology. They are constituted by small dedicated biotechnology firms (DBFs), by LDFs, mostly pharmaceutical but sometimes belonging to other sectors, and by public research institutes (PRIs). These three types of actors interact by forming alliances one of whose main objectives is the creation of new knowledge. These networks were studied during the period 1973–1999 using data from the RECAP database (Catherine, 2005). INs are part of a class of inter-firm alliances which emerged starting from the early 1980s. At that time INs were considered by many economists a temporary form of industrial organization. Existing economic theories predicted that only markets and hierarchical organizations could be stable. Inter-firm alliances were considered a temporary response to shocks, a response which would have disappeared once the shocks had been absorbed by the economic system. Yet, 25 years later the number of INs keeps increasing (Fig. 2.6). INs seem to have become a new and stable form of industrial organization. However, the full answer is more subtle than that.

If we break down the whole period 1973–1999 into two sub-periods distinguished by the main technologies used in each one, the picture becomes considerably different. If we consider that modern biotechnology was created by the potential industrial applications of molecular biology, we can distinguish in its subsequent evolution two generations of biotech, linked to recombinant DNA and monoclonal antibodies and to genomics, respectively. The former begins in the mid-1970s and the latter in the mid-1980s. By classifying all the technological alliances in the data set as belonging either to the first or to the second generation, we can plot separately curves describing their numbers, represent separately their networks and measure properties of these networks, such as density, centrality (Figs. 2.15, 2.16 and Tables 2.2 and 2.3). A number of interesting results emerge:
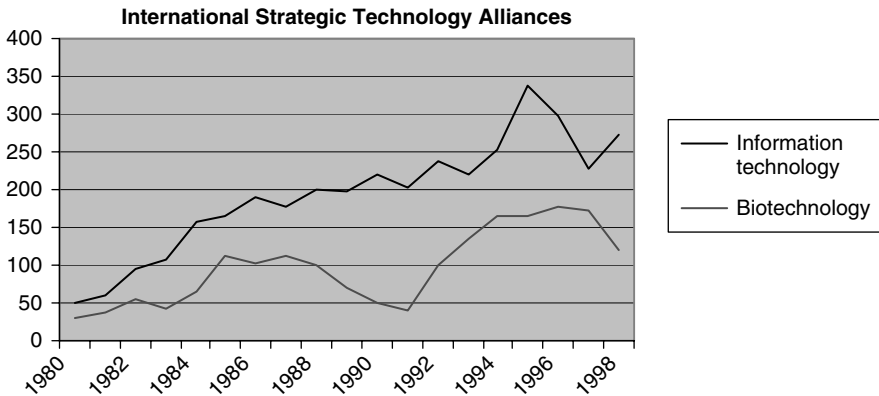
Fig. 2.6 Evolution of the number of technological alliances in ITC and in biotechnology

Table 2.2 Centrality of the different actors (DBFs = PM, LDFs = GGI, PRIs = INS) involved in the first generation of biotechnology alliances

First-generation biotechnology	Period 1976–1984			Period 1985–1992			Period 1993–1999		
Actor's type	DBFs	LDFs	PRIs	DBFs	LDFs	PRIs	DBFs	LDFs	PRIs
Average number of agreement	5.67	3.20	2.63	6.20	10.79	2.61	6.12	15.50	2.05
Average Ndegree centrality	5.84	3.30	2.71	1.71	2.97	0.72	1.41	3.58	0.47
Median Ndegree centrality	3.09	2.06	2.06	1.10	1.38	0.55	0.92	1.73	0.23
Average betweeness centrality	4.95	2.82	0.85	0.71	1.38	0.20	0.40	1.40	0.10
Median betweeness centrality	1.17	0	0	0.20	0.53	0	0.07	0.18	0

- First, the total number of INs in biotechnology keeps increasing (Fig. 2.7).
- Second, the number of INs corresponding to the first generation reaches a maximum in 1996 and then starts declining (Fig. 2.8).
- Third, if in each generation we separate the alliances linked to R&D from those linked to marketing we see that they have a different dynamics. In particular, alliances related to R&D dominate in the early phases but peak out and decline later, while marketing alliances emerge later but dominate the late phases of the life cycle of the biotech generation we are considering (Figs. 2.9 and 2.10).

One of the most interesting results of this study is that INs in each generation of biotechnology follow a life cycle, in which the number of INs rises at first, reaches a maximum and then declines. In the meantime, the type of agreement changes from R&D to marketing passing from the early to the late phases of the life cycle.

Other interesting results emerge when we represent graphically the INs corresponding to the two generations (Figs. 2.11, 2.12, 2.13 and 2.14). Here, we can see that for each generation both the number of nodes and the number of links rises during the life cycle. However, the density of links seems to be falling all

Table 2.3 Centrality of the different actors (DBFs = PM, LDFs = GGI, PRIs = INS) involved in the second generation of biotechnology alliances

Second-generation biotechnology	Period 1985–1992			Period 1993–1999		
Actor's type	DBFs	LDFs	PRIs	DBFs	LDFs	PRIs
Average number of agreement	5.98	5.90	5.48	12.50	25.13	9.27
Average Ndegree centrality	2.48	2.45	2.27	1.68	3.38	1.25
Median Ndegree centrality	2.08	1.66	1.66	1.21	1.55	0.81
Average betweeness centrality	2.70	2.21	2.69	0.41	0.97	0.13
Median betweeness centrality	1.91	1.36	2.14	0.18	0.15	0.07

Evolution du nombre d'accords au sein de l'industrie des biotechnologies
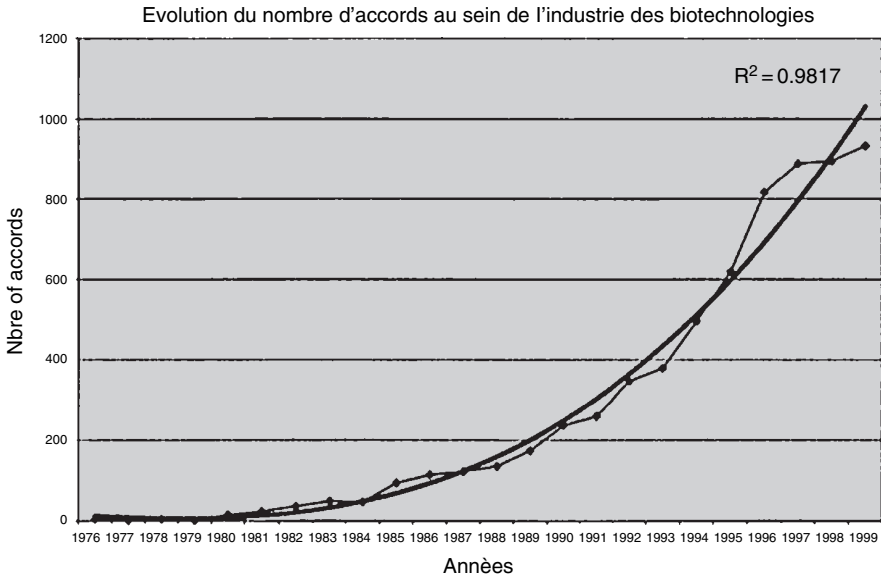
Fig. 2.7 Total number of agreements in biotechnology 1973–1999

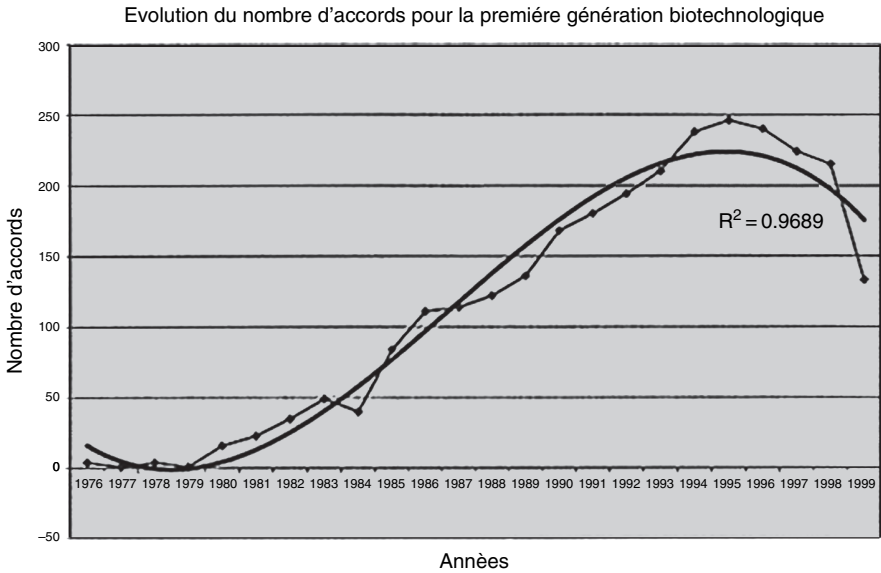Evolution du nombre d'accords pour la premiére génération biotechnologique

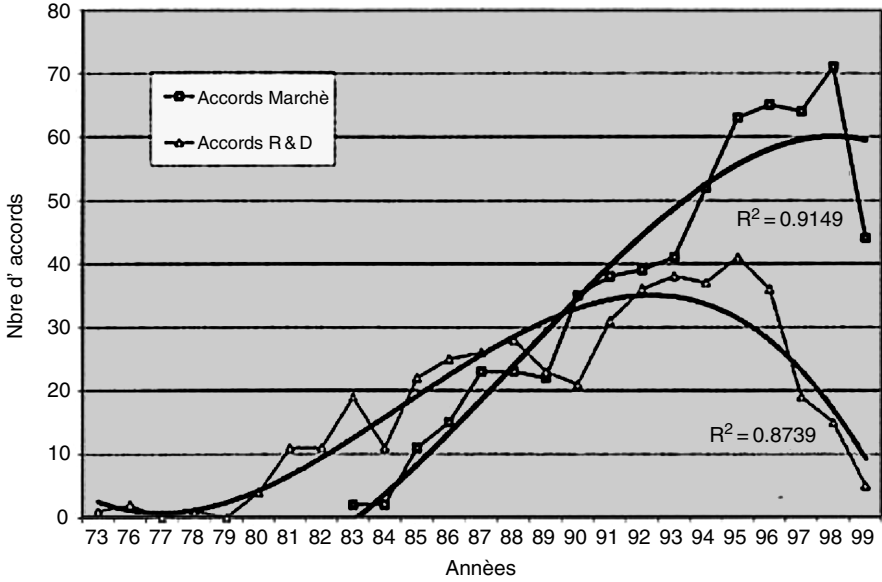**Fig. 2.8** Number of agreements in the first generation of biotechnology

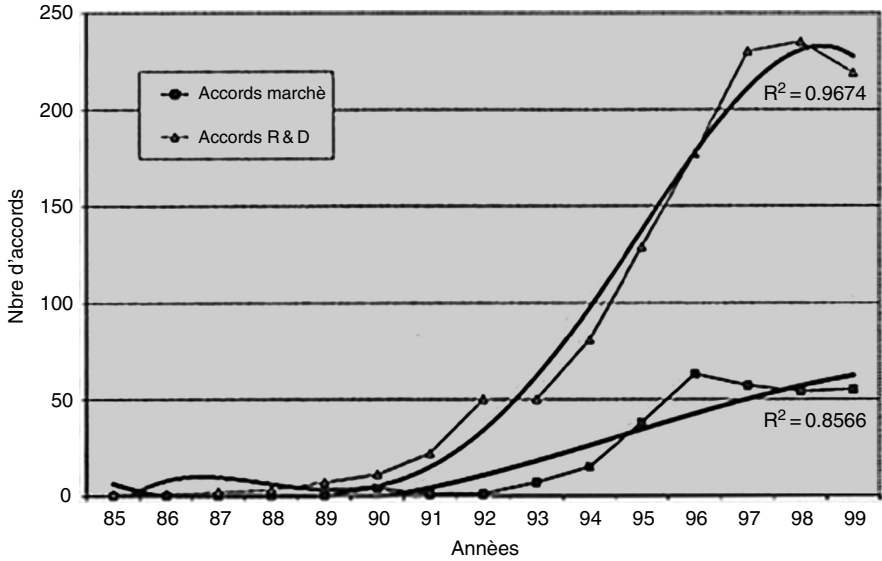**Fig. 2.9** R&D and marketing agreements in the first generation of biotech

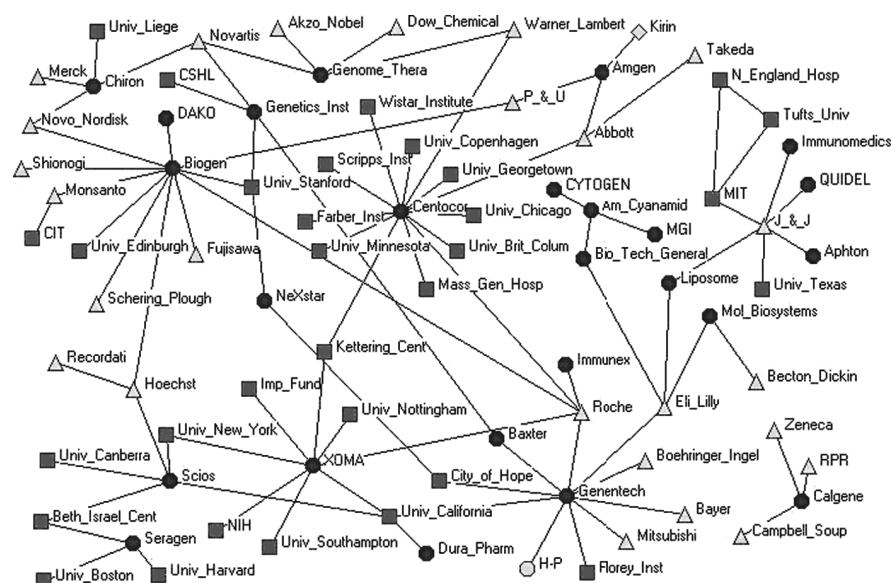**Fig. 2.10** R&D and marketing agreements in the second generation of biotech

Fig. 2.11 Networks, first-generation biotech, 1973–1984

● NEB   ■ Instituts   △ Grands Groupes Industriels
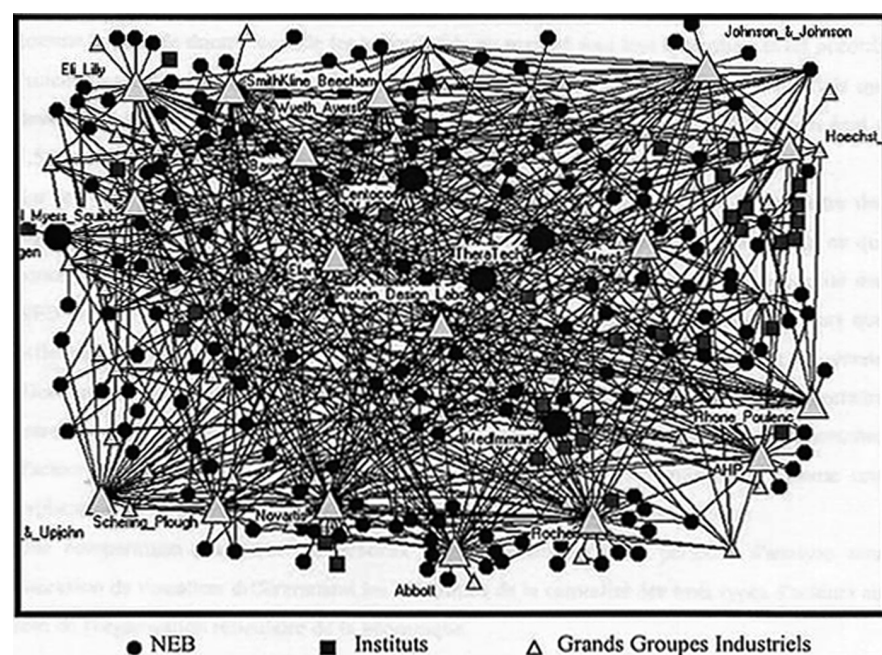
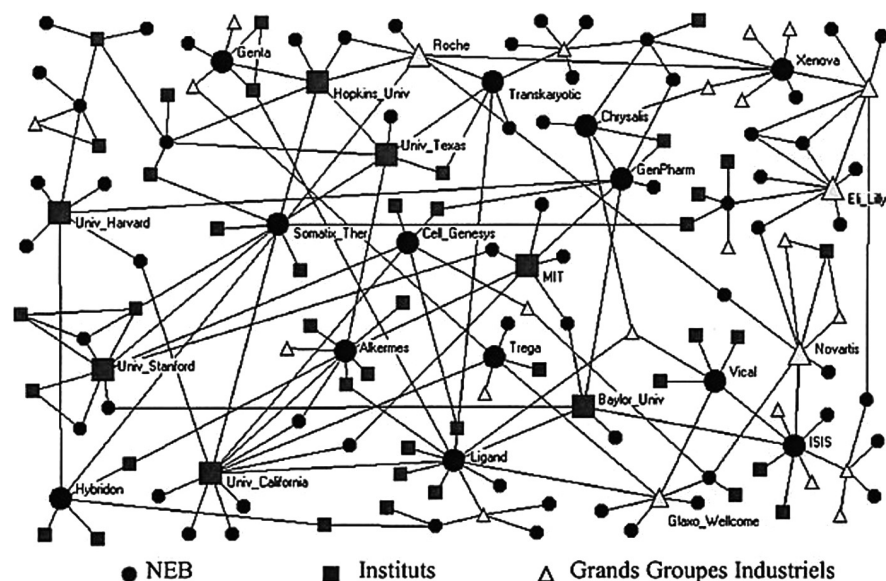**Fig. 2.12** INs, first-generation biotech, 1993–1999

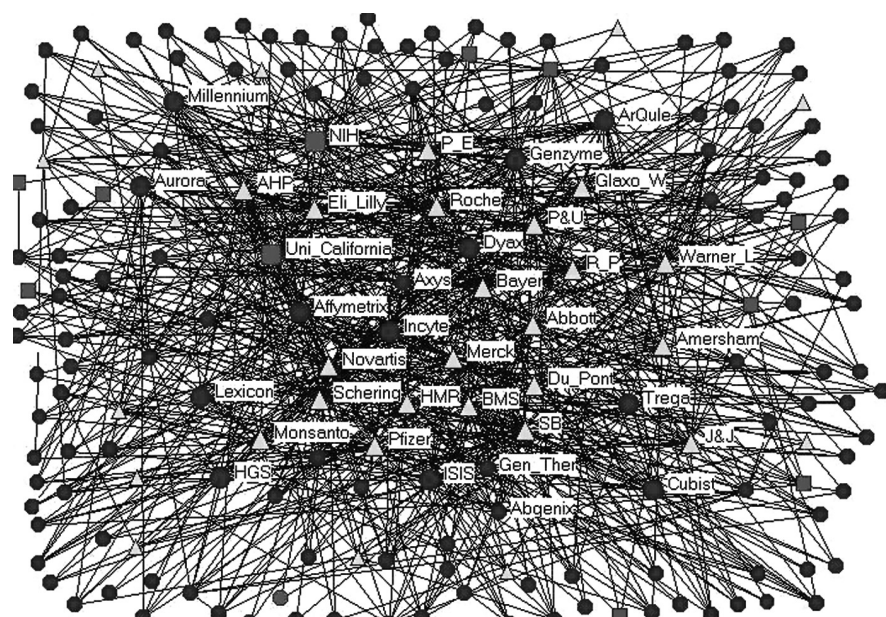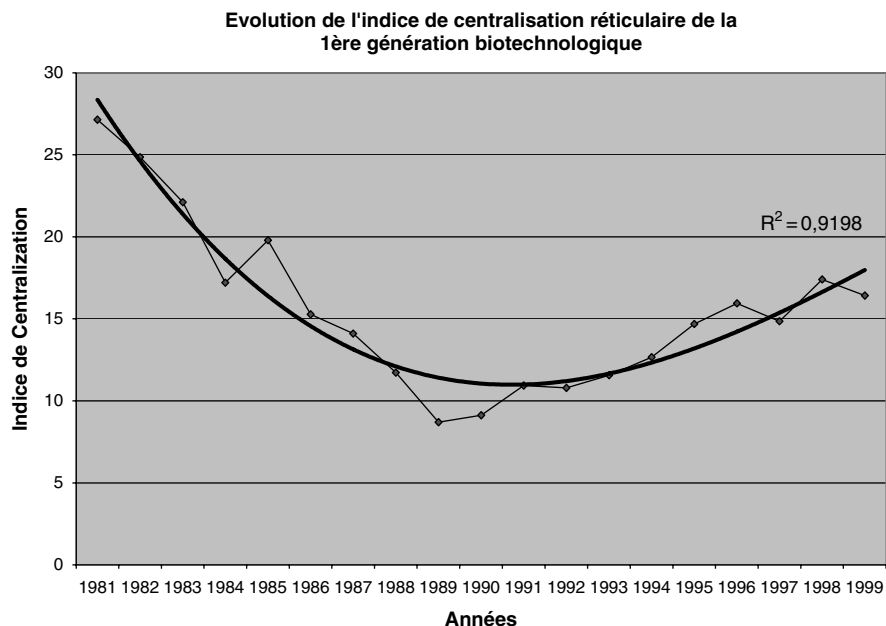**Fig. 2.13** INs, second-generation biotech, 1985–1992

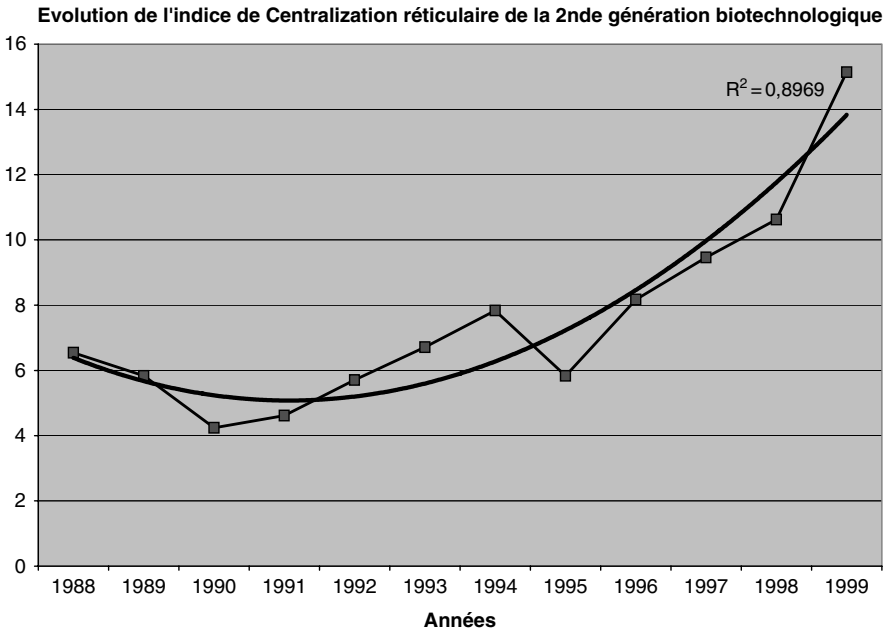**Fig. 2.14** INs, second-generation biotech, 1993–1999

Fig. 2.15 Evolution of network density for the first-generation biotechnology

throughout the life cycle, with the possible exception of the very late phases of the first generation (Figs. 2.15, 2.16 and 2.17).
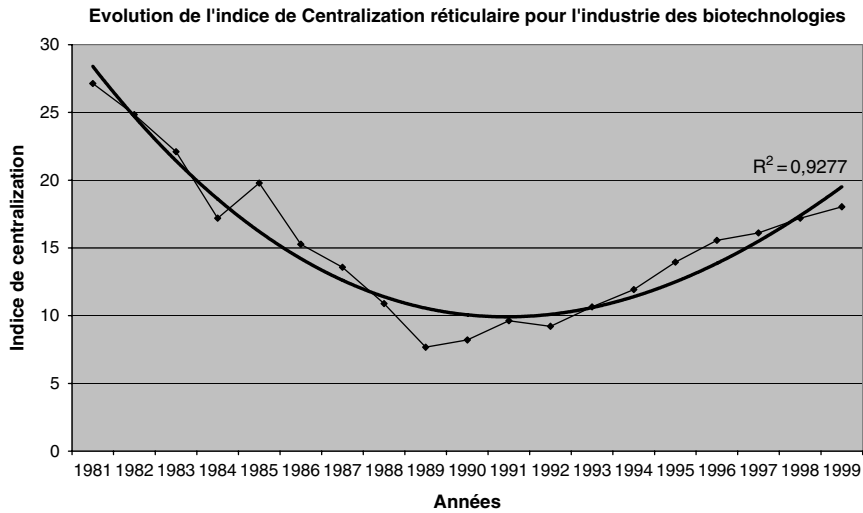
Finally, the centrality of the different actors changes during the evolution of the life cycle (Tables 2.2 and 2.3). The Ndegree centrality of DBFs (PM) is high initially and tends to fall as the life cycle tends towards maturity, that of LDFs (GGIs) falls slightly while remaining rather high, that of PRIs (INS) is initially high but falls to the lowest values of the three actors. The first and second generations show qualitatively the same type of evolution but differ for the relative extent of decline as the life cycle moves towards maturity: in the case of genomics the Ndegree centrality shows a more moderate fall, perhaps due to the shorter duration of the period studied.

Summarizing the results of this section we could say the following:

- INs in biotechnology seem to undergo a life cycle in which the number of alliances rises at first, reaches a maximum and then declines. During the same life cycle, the character of alliances changes from mostly R&D based in the early phases towards mostly marketing based in the late phases.
- This cyclical behaviour can be observed only at the level of aggregation of the generation of biotechnology (1st = Recombinant DNA+monoclonal antibodies, 2nd = genomics). The overall time profile of the number of alliances shows a continuous growth.
- The networks of both generations of biotechnology show an asymmetrical distribution around nodes. The distribution has not yet been measured.

Evolution de l'indice de Centralization réticulaire de la 2nde génération biotechnologique

$R^2 = 0,8969$

Années

Fig. 2.16 Evolution of network density for the second generation of biotechnology

Evolution de l'indice de Centralization réticulaire pour l'industrie des biotechnologies

Indice de centralization

$R^2 = 0,9277$

Années

Fig. 2.17 Evolution of network density for the two biotechnology generations combined

- During the life cycle observed so far, the number of nodes grows and the number of links grows but network density seems to fall.
- The Ndegree centrality of the different actors involved in the networks (DBFs, LDFs, PRIs) tends to fall at different rates, that of LDFs remaining the highest in the long run.

A short comment is required here to interpret the meaning of network density in this case. The creation of new nodes is here due to the creation of new firms. At the beginning we can expect these firms to be relatively poorly connected to the existent economic system. Their early emergence can be expected to be accompanied by a low density of their networks, thus reducing the overall density of the networks in which they can be embedded. However, in order to grow the new firms have to establish interactions with dealers, regulators, customers, suppliers etc., thus leading to a growing density of their networks. The same situation is likely to apply to all firms in new, emerging sectors. Thus, we can expect new sectors to start with low-density networks and to undergo a growth of network density as they mature. In this sense, we can expect new sectors to benefit from the growth in network density occurring during their maturation, although this greater density will also imply a greater difficulty of introducing into the sector further innovations, especially if they are challenging the existence of the links already formed in the network. Of course, the same reasoning can be expected to apply to the technologies which give rise to the creation of new sectors or sub-sectors, as in this case. In fact, one of the main reasons for which network density can be expected to behave in the way described above is the role played by knowledge in the creation and in the dynamics of industrial sectors.

2.4 Conclusions

In this contribution, we studied the properties of a number of knowledge-related networks and tried to interpret them in the light of some recent literature on complexity and on networks. The existence and properties of networks can find their roots in more general theories of complexity, such as that of Prigogine. According to these theories the emergence of structure, or order, in a system requires the system to be open and therefore away from equilibrium. Furthermore, transitions involving changes of structure in the system occur as the open system moves further away from equilibrium. Networks, constituted by nodes and links, can be considered the structure of socio-economic systems. Thus, both their existence and their transitions can in principle find an explanation if they are open systems away from equilibrium.

In general, we can expect the number of distinguishable networks in an economic system to grow as the variety of the same system grows. Furthermore, we can expect the connectivity/density of a network to vary in meaningful ways, for example to fall during the emergence phase of new structures and to rise during the subsequent phases of diffusion and maturation. The connectivity/density of a network can be expected to involve both advantages and disadvantages. Advantages can be

the greater ease of connecting different variables and the greater economic scope acquired by new firms when they improve their links to the rest of the economic system. Disadvantages are the growing rigidity of highly connected networks and the consequent difficulty in introducing into them further innovations. In Schumpeterian terms one could expect the entrepreneurial activity leading to innovations to be accompanied by a low network density and the subsequent routinization of innovations to be accompanied by a growing network density.

The actual networks of knowledge we studied tend to confirm a number of these expectations:

- In general, they show not only a heterogeneous distribution of links around nodes but also a highly asymmetrical distribution of strengths or intensities of the links.
- The conditions required for the existence of scale-free networks are generally present. In particular, during the emergence phase of new structures or of novelty, the number of nodes tends to increase rapidly.
- As a consequence, the connectivity/density of the network tends to fall during the emergence phase and to fall during the subsequent phases of diffusion and maturation.
- The expected time path of connectivity/density is more likely to fluctuate than to rise uniformly.
- We can expect a meaningful relationship to exist between variety growth and network dynamics. As pointed out above, the emergence of new economic species, giving rise to a growing variety, is likely to be accompanied by a fall in connectivity/density while the subsequent phases of diffusion and maturation are likely to see a rise in connectivity/density.
- Since variety only measures the number of nodes, the addition of connectivity, based on the interactions of the components of the system, provides us with a more complete analysis of the evolution of the complexity of a socio-economic system.

This contribution is much more speculative than definitive, concentrating on possible generalizations of the role and dynamics of socio-economic systems. A considerable amount of further work will be required to test and articulate the propositions suggested in this contribution. However, it seems that the themes treated are of central importance to understand the complex dynamics of socio-economic systems, in particular as we move towards a knowledge-based society.

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