Complex Networks Theory and Agent-based Social Networks

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Abstract

The final version of this draft is intended to be a working paper for the CAVES[1] (Complexity, Agents, Volatility, Evidence and Scale) project as well as part of the Centre for Policy Modelling Discussion Papers series, and would be available online.

This note surveys some of the most important concepts in the field of the so-called ‘complex networks’, and some classical and recent applications in various disciplines. Social networks are introduced in Section 2, and an overview of the traditional analysis techniques is presented. Section 3 addresses the issue of the techniques and issues that arise in the fieldwork research about social networks. We discuss, in Section 4, some recent critique of the traditional social networks analyses techniques and the ideas to tackle their dynamics, as presented researchers in the field. Finally, Section 5 discusses the used of agent-based modeling in the study of social networks.

Keywords
Complexity, complex networks, agent-based social networks

1 Theory of Complex Networks

This section begins with an attempt to explain complexity as defined by researchers in the relevant fields. We present the notion of ‘complex networks’ in general, followed by a discussion on the most important characteristic networks. The section ends with a quick overview of some recent applications of the complex networks theory in various disciplines.

The enormity of the size of networks in quite a few real-world applications, gave rise to a new surge in multidisciplinary research under the term called ‘complex networks’. The term umbrellas the size, similarity of structure and dynamics in the observed networks, which belong to a variety of disciplines, from natural and physical sciences, social sciences to the Web. In the last decade, extraordinary advancements have been made in the studies of complex networks. The studies have resulted in identifying characteristic networks and their relevant measures. A comprehensive review may be found in (Newman, 1999; Albert and Barabási, 2002).

1.1 Complexity and complex networks

The crux of the CAVES project is ‘tackling complexity’ (CAVES, 2005) and it may be useful to present its notion in the context of aims of the project. Networks emerge when subsystems or in terms of social system, actors, are linked with respect to some relations. The idea of

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complex networks has been around for almost a decade now, which we discuss in the subsequent section.

1.1.1 Complexity

To begin with, the Merriam-Webster dictionary (2005) defines the term 'complex' (we pick the most relevant variant) as:

Definition: Complexity

> *"a group of culture traits relating to a single activity (as hunting), process (as use of flint), or culture unit b (1): a group of repressed desires and memories that exerts a dominating influence upon the personality (2): an exaggerated reaction to a subject or situation c: a group of obviously related units of which the degree and nature of the relationship is imperfectly known"*

Our purpose here is to present the notion of complexity that arises as a result of interaction among actors (individuals, organizations, etc.) which in most cases is localized, but leads to the emergence of patterns that would be hard to predict given the simple nature of the rules-of-interaction. Complexity, complex systems and all sorts of relevant terms have appeared extensively in the contemporary scientific and philosophical literature, e.g. Edmonds (2001) define complexity which can be used in the context of the 'level of difficulty' involved in modeling the behavior of a natural or artificial system.

Definition: Complexity as defined by Edmonds (2001)

> *Complexity is that property of a model which makes it difficult to formulate its overall behaviour in a given language, even when given reasonably complete information about its atomic components and their inter-relations."*

In the context of social networks and general study of networks *per se*, the notion of complex is concordant with the notion of the size of the network. Moreover, one may also identify complexity as a phenomenon associated with the interactions (or relationships) among individuals and/or their interactions with the environment. We end our brief discussion on complexity on the following (relatively old) quote by Cordell (1986):

> *"The rate and magnitude of change are rapidly outpacing the complex of theories – economic, social, and philosophical – on which public and private decisions are based. To the extent that we continue to view the world from the perspective of an earlier, vanishing age, we will continue to misunderstand the developments surrounding the transition to an information society, be unable to realize the full economic and social potential of this revolutionary technology, and risk making some very serious mistakes as reality and the theories we use to interpret it continue to diverge."*

1.1.2 Complex Networks

Networks have been studied formally at least as early as from the 18th century, where Euler pioneered the Graph Theory in his attempt to solve the famous Königsberg bridge problem.

Graph theoretic concepts have been applied ever since in various disciplines where there are a set of entities linked by means of some relationship. Investigating the structural properties of such networks has led to a whole range of analytic measures that form the basis of the modern graph theory. Application of such analysis tools in social sciences can date back to the start of the 20th century (Scott, 1991), in which ever since, the discipline of social network analysis (SNA) has stemmed as a result of the research of networks involving *actors* (individuals, organizations, etc.) and development of a metrics focusing on different aspects of social positions and interactions. We will discuss SNA in Section 2 of this article.

1.2 Typical Complex Networks and Characteristics

We present only a brief overview of the typical complex network characteristics and their salient features. An exhaustive literature is available, especially (Barabási, 2001; Watts, 2003) provide a comprehensive account of the networks.

1.2.1 Random Graph Theory

One of the earliest attempts to study the behavior of these so-called 'complex networks' dates back to the seminal work on random graph theory by Paul Erdös and Alfréd Rényi, (the so-called E-R model) in the 1950s.

The basic E-R model requires connecting N nodes through n edges chosen randomly such that the resulting network is from a space of $C^{n}_{N(N-1)/2}$ graphs, each equally likely. Several nodes can have the same degree in a random graph (large enough) which can be calculated. Given the probability of wiring p is not small, the diameter of random graphs is usually small and the diameter increases logarithmically, as a random graph evolves.

1.2.2 Pareto Distribution and Self-Organized Criticality

The underlying assumption in using the statistical methods, in many situations, is that the mean and standard deviation of the distribution of the data are known and are stable. In many cases, it was found that the simulation results in generation of data that has a fat-tail and thin-peak: a characteristic known as *leptokurtosis*.

One of the most studied characteristics of the complex networks is the appearance of the power-law distribution in many areas. Informally, it means that the most connected nodes in the network are relatively very few as compared to the lesser connected nodes (or vice versa). The so-called power-law(s) stem from the *Pareto Distribution*, a specialization of the *Pareto Principle*, named after Vifredo Pareto (Wikipedia, 2005). The probability density function of the distribution is defined as:

$$f(x;k,x_\mathrm{m}) = k\,\frac{x_\mathrm{m}^k}{x^{k+1}} \text{ for } x \ge x_\mathrm{m}.$$

The distribution is parameterized by two parameters: x_m and k. As Barthélémy (2003) discusses, if the shape (peakedness) parameter $k \in (0, 2]$ has value $k \le 1$, the mean is infinite; while for $k \le 2$ the variance is finite. Figure 1 shows the thin peakedness, which is the characteristic of the distribution. Our purpose is here is about the implications and not presenting a discussion on the analytical properties of the distribution, which can be found in any standard text on stochastic distributions.

One implication of the appearance of statistical properties like the power-law etc., is that they provide useful guide to analysis of multiagent based simulation of social phenomena (Moss *et al.*, 2000). Such characteristics provide cues for further investigation of the underlying model and the phenomenon it addresses. We will come back to this issue later in this article. Another implication identified by *ibid* was that "the specification of utility maximising agents will not support an analysis of the properties of large, distributed systems if those systems are to mimic market systems as described by equilibrium economic theory". This further encourages in looking for statistical signatures in validating the relevant theories. The fact that higher, thinner peak of the frequency distribution with respect to the corresponding normal distribution, i.e. leptokurtosis, are observed in the series of data from quite a few social networks (Moss, 2001; Moss and Edmonds, 2005), provides analysis of such behavior a highly prospective candidate for a thorough investigation. Therefore, it is interesting for both policy designers and modelers to not only identify the causes of volatility and clustering of data, but to look for means to be able to predict (if possible) the phase transition, which may be regarded as policy change, change of political views, etc.

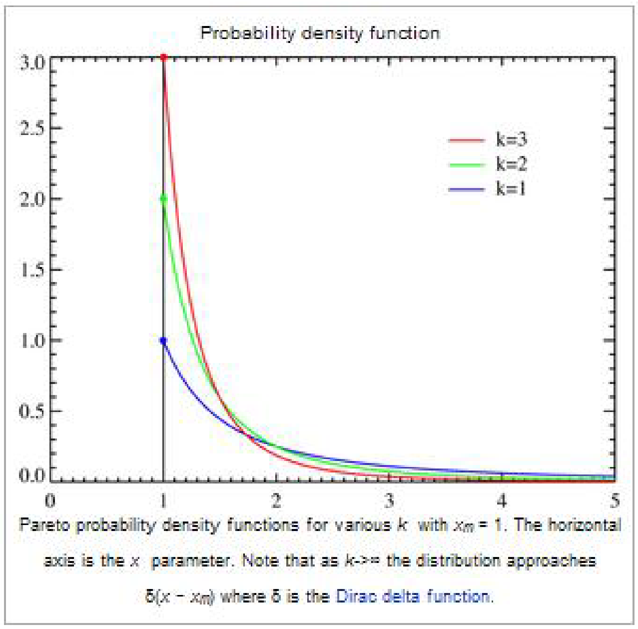

Figure 1: Pareto Distribution; source (Wikipedia, 2005)

Self-Organized Criticality (SOC) maybe interpreted as the response of slowly-driven system such that the outcome of the system's behavior is limited by the magnitude of its size; thus, leading to the *scale-free* property (discussed in the subsequent section). Following Jensen (1998), one may explain SOC as the development of emergent patterns due to the interactions among *meta-stable* agents, such that at some *critical* state, the result of interactions affects the entire system such that 'all members of the system influence each other'. For the rest of the period, the any local distortions resulting from agents' interaction in their neighborhoods remain confined locally.

Several properties of the systems exhibiting SOC have been reported. Moss and Edmonds (2005b) present these properties in the context of a number of cases involving agent-based simulation of social phenomena as:

- Individuals are meta-stable, i.e., they do not change their behavior ‘until some level of stimulus has been reached’. Jensen (1998) insists that SOC cannot be manifested with utility maximizing agents.
- Local interactions are the dominant feature and their effects remain local most of the time.
- ‘Agents influence but do not slavishly imitate each other’.
- ‘The system is slowly driven so that most agents are below their threshold (or critical) states a lot of the time.’

1.2.3 Small-World Networks

As shown by Erdös and Rényi, if the probability of connectedness $p \geq ln(N)$, N being the number of nodes in the network, then one can find a path of edges that connects any two nodes in the network. As the length of the shortest path between two nodes tends towards $O(ln(N))$, which is small, a random graph exhibits the property, the so-called ‘small world’ effect.

A seminal contribution was made by the sociologist Stanley Milgram whose study based on social networks led to the term ‘six-degrees of separation’. The term ‘small world’ thus implies that in most networks (even as large as the World Wide Web), there exists a significantly shorter path between two nodes present in the E-R model.

In 1998, Duncan Watts and Steven Strogatz presented their Watts-Strogatz (WS) model, see Figure 2, which ‘interpolated’ a small world graph as an intermediate of a purely random and a regular graph. The property displayed by the networks had been observed in quite a few social systems such as friendship, coworker networks, conflict networks etc., where the average path length is small and shows high clustering property characterized by the clustering coefficient. Informally, the clustering coefficient supports the phenomenon ‘the friend of my friend is also a friend’ or that the neighbors of a node are more likely to be linked to each other than in a pure random network.

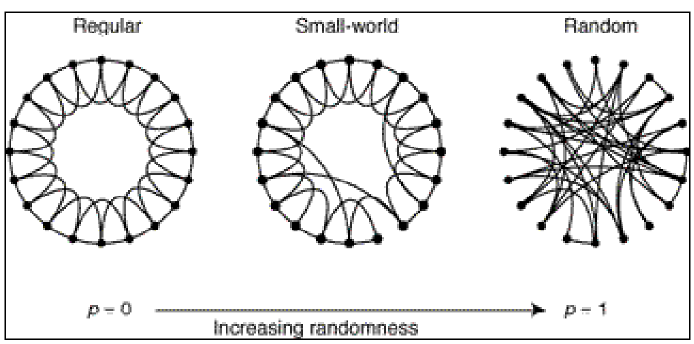

Figure 2: Random rewiring procedure in the WS model. (Albert and Barabasi, 2002)

1.2.4 Scale-Free Networks

As explained by Albert and Barabasi (2002), just using the ER or the WS models just does not capture the two important aspects of real-world networks. First is the assumption that the number of starting nodes is fixed and is not changed. Secondly, in the random networks, the chances of a node being linked to another are equally likely. Real-world networks not only evolve over time but also exhibit the notion of *preferential attachment*, where the likelihood of a node being connected depends upon the number of edges it has.

The Barabasi and Albert model (BA) tackles the two aspects in two steps:

i. *Growth of the network:* This starts with a small number of nodes, say, N and each time step, a new node m is introduced in the network. The new node is connected to the nodes from N.

ii. *Preferential attachment:* The choice of nodes to which $m(\leq M)$ is connected, the probability that m will be connected to a node $n \in N$ depends upon the connectivity of the node such that,

$$\Pi(k_i) = k_i \Big/ \sum_j k_j$$

After t $(\leq T)$ time steps, the model evolves to a networks with $t + m$ nodes and Mt edges. As demonstrated Albert and Barabasi (2002), the network evolves into a 'scale-variant' state such that the degree distribution follows a power-law, with the scaling component independent of M.

2 Social Networks Analysis (SNA)

Over several decades researchers have used social networks study methods either to investigate the patterns that emerge from in the interaction among people belonging to various kinds of networks, e.g. kinship, work, friendships etc; or to identify the major *actors* or nodes in the network which influence the structure of the network in a number of ways. It is important to note that despite the fact that social networks research is described in terms of the repertoire of the measures, it has a long history of qualitative research. Social networks, maybe regarded as important sub-discipline in the social sciences in broader terms. Hence studies in social networks range from pure qualitative research to development of sophisticated quantitative metrics that capture the macro-properties of the underlying network.

As we shall present the arguments raised by several researchers recently later in this article, that the any authentic evidence reported in a case-study comes before any analytically imposed structure when modeling social networks. This important characteristic of social networks distinguishes them from complex networks structures found in physical and biological systems.

3 Issues in Social Networks Fieldwork Research

While in principle, any social network research should be based on the empirical evidence, acquiring real-world is one of the most challenging tasks for the field researchers. Unfortunately, this often leads to analysis of networks formulated on either very small data sets or some *a priori* set of hypotheses, which is even worse. A major obstacle is the often unwillingness (for any reasons) of the stakeholders to feed-in the researchers, especially when the questions are concerned about their relations (or lack of it) with other stakeholders in a case study area. Another obstacle is the unavailability of funding to do fieldwork research; which could either lead to the paying less heed to study real-world social processes or the unjustified assumption that the available aggregate data adequately represent the stakeholders' behavior.

As Schensul *et al.* (1999) identify, some of the social networks descriptions based on case-studies include the following:

1. Identification of people in them
2. How groups members are defined by the people
3. 'The rules people use for including and excluding members'
4. Familial and sexual relationships, (if any), within the groups etc.

A primary objective for fieldwork researchers is to identify the *boundaries* of social groups that exist among the actors or the stakeholders and investigating the features that distinguish them.

***Definition: Boundaries* from Schensul *et al.* (1999)**

> ***"****Boundaries constitute the edges of networks and are defined by rules for entry and exit from groups as well as by other cultural patterns of participation that differentiate one group from another."*

As Schensul *et al.* recommends, it is really important to interview as many as possible people in the case-study areas, as people's views about their acquaintances and their groups help in identifying the inclusion/exclusion, closeness/openness within and among the groups. Returning to the notion of *neighborhood*, physical neighbors maybe described in terms of the land use, segregation of sub-regions etc. while the social aspect of neighborhood is based on the 'local social interactions, social class, ethnic and radical origins, life cycle characteristics of the population, length of residence, and place of work' etc.

A focus of any evidence-based research is the *community*, a social unit, where people share common 'values and needs' and/or similar ideologies. As the concept of *locality* is embedded in its definition, a community may be identified as sharing social characteristics or as *community space*, where the interactions take place, or both. Local interaction among neighbors has been a subject of quite a few agent-based social simulations, and as we shall discuss later on, a number of such simulation models are inherently spatially explicit. One natural unit in a community space is the *household* or a cluster of households, e.g. in extended families etc. Identifying the community space and distinct regions is vital, especially in the context of modeling land-use changes etc. (LUCC, 2001)

As Bailey and Gatrell (1995) explain, "spatial data analysis is involved when data are spatially located *and* explicit consideration is given to the possible importance of their spatial arrangement in the analysis or interpretation of results." Spatial analysis, for example those based on GIS (Graphical Information Systems) techniques highlight the importance, provided it exists, of neighborhood or influences, if any, in the actors' behavior caused by the spatial-context. Schensul *et al.* (1999) has thoroughly covered the issues involving spatial mapping of data; we however, restrict to reporting a few most relevant points. For any social networks, the atomic units are obviously the individuals. In gathering data about individuals, it is quite useful to identify the general spatio-temporal constraints that limit most individuals' movements and interaction in the region.

An important facet of a community, imminent for investigating social networks, is the existence of so-called 'community organizations', which operate within the perimeters of the community. Such organizations maybe identified in terms of their membership types (e.g. open, by reference, etc.), the services they offer (e.g. social, economical, etc.) and the minimum threshold of the number of members, and other factors. Such organizations can be state-managed, non-government organizations (NGOs), or loosely-coupled local clubs etc. For public or state-owned organizations, which usually serve for the general welfare of the inhabitants in a community, it is relatively easier to obtain data, than otherwise. In case of the local private clubs, dedicated to specific interests of their members, acquiring data is certainly a non-trivial task as people usually avoid disclosing their private social activities and affiliations. However, with respect to the social networks in the community, such local clubs are the building block and hence are most important to be investigated. A major difficulty in this regard is the local people's mistrust to the fieldwork researchers, especially if the neighborhood is hard-pressed and poor. As the effects resulting form a qualitative research in social networks are not visible immediately, people tend to think such practices as waste of time and perhaps exploitation. It is therefore, of immense importance, that the researchers involved in qualitative social networks fieldwork, are supported with sufficient time and funds, so that they maybe able to gain the confidence of the local people, by staying and involving them as well. An interesting methodology involving the 'players', is the setting up of 'role-playing games', which we briefly review later in this article.

Psychological and Ethical Issues in Gathering Evidence

Concealing information could either due to the individual's involvement in illegal activities etc., or in many cases as an effect of 'stigmatization'. A major problem in uncovering the socioeconomic impact of HIV/AIDS and other sexually-transmitted diseases (STDs) is the people's fear of social condemnation, social boycott and alienation from the community, resulting in the ruin of the entire household. Quoting from Ziervogel *et al.* (2005), sheds some light on how such social stigmas affect an ordinary individual's life.

> *"In Zambia there is stigma in the village with regards to HIV/AIDS. They say they can only go for VCT if they are sick. 'Why should I go if there are no drugs to treat me?' People are not talking about HIV/AIDS, as people would rather talk about something else. They want to distance themselves from the disease. If you have a poor life and you are already burdened why would you want to go for a test and find out you are HIV+ and then become more burdened? What is the incentive if they are not able to access services or drugs and they know that if they tell one person, then the whole village will know? Parents are also concerned that if their status is known, then people might be prejudiced against their children and not feed them if they go to beg for food."*

4 Towards Non-Traditional SNA

Recently, the social network analysis community has been concerned over the use (and misuse) of metrics and validation techniques for both the empirical and simulated networks. With the plethora of available measurement tools, it has become immensely important to choose carefully the most suitable set of metrics depending upon the context of the underlying study. For example, whether it is about the spread of disease, asymmetric information exchange, dyadic friendships relations etc; especially, when identifying the key players in case of transmission. Hence whether the data are directed or undirected, the nature of the network and the context are important.

SNA is not a method but a paradigm (from the SOCNet Mailing List Archives):
Whether social network analysis is a paradigm or just a method is still arguable in the community. Some researchers have preferred calling it as just 'network analysis' that covers most types of networks and not just social contacts. This is in line with Carley's DNA Matrix (Carley, 2003), where networks comprises not just of people, but among organizations, institutes etc. Another view is about considering SNA as a set of measures applied to understand various facets of networks. However, a strong part of the community does not see it as merely a set of analysis tools, but a way of looking at things where networks play the central role. As Steve Borgatti reports in one of the postings, networks research is 'distinguished first and foremost by the subject matter - what we study - which is networks'. Data collection and empirical evidence thus remains vital in any kind of network analysis. Thus network analysis as a field is characterized by the underlying context and the nature of relations that exit among the entities.

Borgatti and Mehra (draft) have recently addressed the four major criticisms on the traditional social network analysis. We present only their assessment related to dynamics and 'agency', briefly; details can be found in the original paper. The traditional structuralist approach has invited the criticism that network research is static and thus only the outcome are focused, and ignoring the factors that have caused evolution of the network. Nevertheless, with respect to the notion diffusion of information and the social impact, it is not only supported by strong theoretical basis, but also these concepts have led to the development of quite a few analytical and graphical analysis tools. Concerning the role of agency, we discuss the issue at length in the next section.

5. Agent-based Social Networks (ABSN)

Agent-based simulation models of social phenomena date back to the mid 1980s. As Axelrod (1997) argues, the goal of this modeling approach has been to break simplistic assumptions required for mathematical tractability, e.g. homogeneity, ignoring interaction. With the advent of multiagent models, social simulation benefited from it most as these models provided the provisions of simulating social behavior of autonomous individuals and the interactions among them. Agent-based models have been accredited, in most cases, as suitable for decentralized scenarios, especially when individual interactions lead to the emergence of collective patterns, like in the case of complex social networks.

5.1 Spaces and Social Embeddedness

The importance of signifying boundaries and neighborhoods has been discussed in the previous section. Modeling a social network requires identifying the spaces in which the agents exist and are related. All relations among real entities exist and are constrained through physical spaces. More importantly, case-studies involving land use change, distribution and utilization of physical resources are modeled spatially explicit *per se.*

Typically, in spatially explicit models, agents may include stakeholders, land owners, farmers, public institutions, policy or decision-making agencies. Moreover, as Brown (in press) elucidate on such models, the behavior of such agents, may vary from being triggered by some external stimulus or coping with certain stressors, to being goal-oriented. Especially, with regards to models incorporating land-use change, several criteria have been suggested for being *spatially explicit*, e.g. (LUCC, 2001) as follows:

- *Invariance Test:* the model is spatially explicit if the results are not invariant when the understudy objects' positions are changed.
- *Representation Test:* requires explicit representation of the system in the model, e.g. use of spatial coordinates, GIS, etc.
- *Formulation Test:* the model satisfies the test if the modeled spatial concepts are formulated as rules.
- *Outcome Test:* a spatially explicit model modifies its *landscape*, i.e., the spatially forms of input/output are different.

Modeling dynamical social networks where agents communicate with each other and build relations over time require the introduction of 'social' spaces that go beyond the physically situated agents. Such agents can be called 'socially embedded' (Granovetter, 1973; Edmonds, in press), i.e. an agent's behavior is fairly influenced by the network of social relations that it is part of. Physical resources and interaction with the environment, does not fulfils the demand for capturing the social interactions that may influence, for example, a farmer's decision to plant a certain type of crop, or use of their land. Social spaces and the agents' interactions can either be constrained via local neighborhood, or could just be global (i.e., each agent can be directly related to any other agent in the space). In the former case, the sociability of agents depends upon the spatial neighborhoods and thus as Edmonds (in press) puts it, the physical space is used as a 'proxy' for social space.

An example of incorporating both physical and social spaces, in order to better capture the complexity of stakeholders' interactions, is the 'CCDeW project' by Downing *et al.* (2003), modeling the mutual influence on domestic water demands.

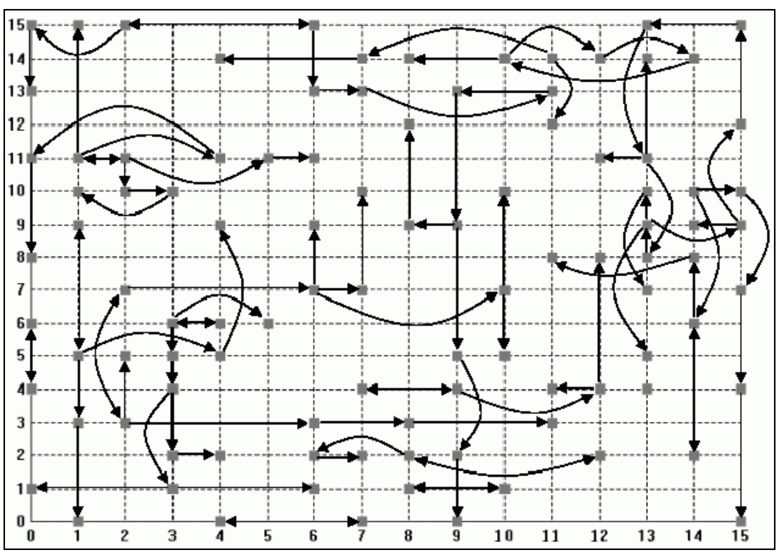

Figure 3: Interplay of Social and Physical Spaces; source (Edmonds, in press)

Figure 3 illustrates the 'social topology' resulting from the neighborhood in the model used in CCDeW. As reported, the results from the simulation clearly show that the social network of the agents (households, in this case) has a significant effect on the 'qualitative nature of the aggregate water demand patterns that result'.

Not many social networks model exploit the combining of both the social and physical spaces, which is pivotal for analyzing the underlying complexity and to which agent-based models are best suited as they support modeling both the spatial neighborhood as well agents' cognition in building relations. Hence, research in the symbiosis of the two 'spaces' has still quite a few niches to be filled.

5.2 Some Other Examples of ABSN models

In this section, we briefly present some of the related work as examples of agent-based models for social networks. The examples are by no means exhaustive; the purpose is to discuss some representative approaches and models by other researchers.

5.2.1 *Dynamic Network Analysis* by Carley (2003)

Carley's *Dynamic Network Analysis* (DNA) introduces the *meta-matrix*, proposes the schema for coping with the problems of multiple relations and co-evolution of both the agents (entities, nodes) and the relationships over time. Moreover, the advancement in this schema, as claimed by the author, are supplemented by the modeling of ties probabilistically, and 'combining social networks with cognitive science and multi-agent systems'. The meta-matrix attempts to capture the interplay between people, resources, tasks and the organizations resulting in *10* inter-linked networks. The idea is that change in one network results in a change in the other and so individuals related in more than one networks implies a tie in the social network. Figure 4 illustrates the meta-matrix where the entries describe the inter-linked networks.

Table 1. Meta-Matrix

	People	Knowledge/Resources	Events/Tasks	Organizations
People	Social network	Knowledge network	Attendance network	Membership network
Knowledge/Resources		Information network	Needs network	Organizational capability
Events/Tasks			Temporal ordering	Institutional support or attack
Organizations				Inter-organizational network

Figure 4: Meta-Matrix; source: Carley (2003)

5.2.2 FEARLUS: A System for Modeling Land Use Change

FEARLUS (2005) is the modeling framework designed for the assessment of land use change scenarios. Built upon the Swarm modeling system (SWARM, 2005), it supports a variety of agent-based modeling techniques and extensions such as hydrological model, land parcel trade, cropping techniques, effect of climatic variability on land parcels etc. A range of parameters and strategies are also implemented in the FEARLUS for modeling land managers' preferences, spatially-explicit representation of the land, a built-in auction mechanism (Polhill *et al.*, 2005), etc.

A significant aspect of FEARLUS is that both the social and physical neighborhoods are coupled, and are represented in the system, which was an important issue discussed in the start of this section. Figure 5 demonstrates the social and physical neighborhoods as used in FEARLUS.

The social neighborhood in the system is used when farmers or owners of the land parcels (the land parcels are represented as cell in the 2-D grid) imitate each other in terms of deciding their strategies. On the left in the above figure, the black border shows the social neighborhood, while the black border on the right side represents the physical neighborhood; the farm is colored in burgundy.

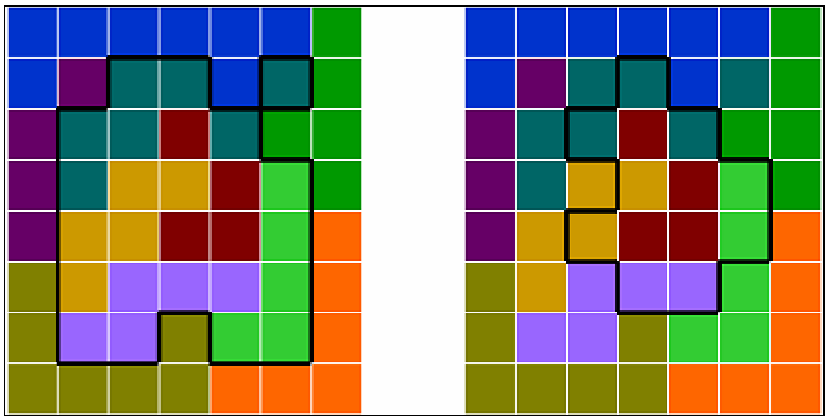

Figure 5: The left image shows the representation of social neighbourhood, whereas the physcial neighbourhood is shown on the right side; source (FEARLUS, 2005)

5.2.3 Role Playing Games

An interesting aspect of social simulation, where the agents (or actors) are actual humans rather than computer-based simulations, can be characterized under the general theme of the 'role playing games' (RPG). Typically, the participants in such designed games are the stakeholders who assume different roles, such as farmers, funding agencies' representatives, etc. As explained by Barreteau *et al.* (2001), "The initial idea is to consider the RPG as a living MAS in which players are the agents and the set of roles is the rule base." The rules are set as simple and are designed based on the conceptual studies of the underlying domain.

Role-playing games in social simulation have a distinctive advantage for the understanding and validation of the MAS model as the stakeholders are the best judge of a model's behavior. Actions represented as rules not only facilitate in explaining the players how to participate, but also support any evidence based modeling of the phenomenon. Figure 6 demonstrates the cyclic relationship of the multiagent systems and the role playing games.

The relation of MAS and RPG allows the stakeholder interaction and their feedback and thus incorporating evidence in understanding the complexity of the system via the agent-based models.

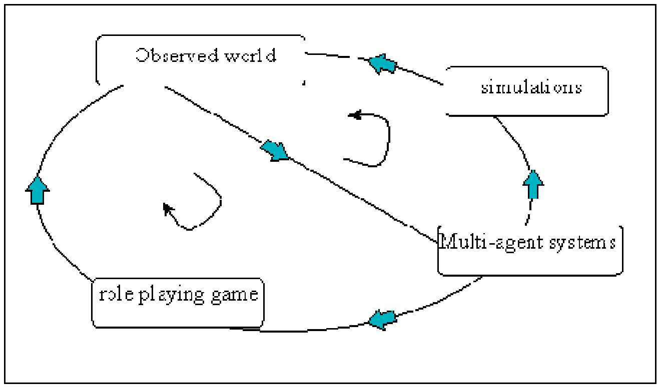

Figure 6: Association of MAS, RPG and field observations in a two-cycle method; source Barreteau *et al.* (2001)

5.3 Modeling Dynamic Social Networks using ABSS

In a recent paper, Edmonds and Chattoe (2005) addressed the perils and prospects of the agent-based modeling of social networks, citing several case studies. They raise two important issues: first, traditional SNA do not have the means to tackle the underlying causal mechanism, and second, it would be misleading to apply social network measures without keeping in view the context over which it had evolve. Several case studies have been presented to illustrate how agent-based simulation can be an effect means to explore these issues.

Stressing upon the concept of social embeddedness (discussed earlier in this section), Edmonds and Chattoe (2005) argue that an agent's behavior cannot just be reduced to the notion of a mere node. Since in complex systems, it is very hard to anticipate how the emerging patterns resulting from interactions at the micro-level, often it is misleading to apply measures on just the statistic 'snap-shot' of the network. As indicated by the authors, the most common ways of applying network measures, i.e. the *post hoc* and *a priori* ways do not help much in resolving the issues. For a *post hoc* way, one has a hypothesis about some social phenomena and thus, a suite of 'suitable measures' are selected to test it. However, this may possibly lead to the danger of choosing 'an abstraction' which may not be the representative of the phenomenon, even though it tends to confirm the hypothesis. In the second way, a network measure is used to understand some phenomena and draw conclusions. This requires *a priori* assumption(s) about the measure that has been applied ignoring the context of the network. A schema has been proposed that makes use of the simulation in order to find better means for abstraction. Figure 7 represents this schema.

Although the proposed scheme only scratches the surface, it does identify the fact that there are quite a few niches to be filled in the research in dynamics of social networks and their analyses. These include:

- Collection of information about the dynamic and generative mechanisms, through stakeholders' accounts, direct observations etc.
- Further questions that need to be asked and information can be obtained following preliminary outcomes of the model.
- Building a 'descriptive simulation', to be validated qualitatively at the micro-level and using *statistical signatures* at the macro-level.

- Establishing the level of abstractness following multiple runs of the simulation and analyzing the generated social networks.
- Determining the measures to 'reflect the important aspects of the resulting social networks' and testing them accordingly.
- The measures could be applied back to the original phenomena in order to establish their 'effectiveness and generality'.

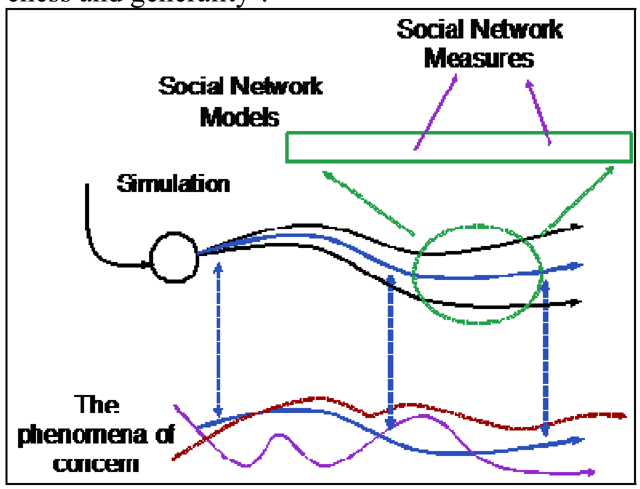

Figure 7: An illustration of the use of simulation to stage abstraction; source (Edmonds and Chattoe, 2005)

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