Abstract

HIV/AIDS has long been understood as the major obstacle in human development, especially in the poorest regions such as the sub-Saharan countries in Africa. However, most people in this region regard other stressors, e.g. food insecurity, high increase in adult deaths, unavailability of irrigation water, lack of grants, etc. as the major causes of their distress. This is part of an ongoing project that attempts to model the complexity that arises as a result of actors’ interactions at the individual and the household level. The model addresses several issues in understanding how such stressors, in particular, HIV/AIDS, affect the community structure. Networks that result from social processes in simulation are dynamic and co-evolving in nature. In this paper, we outline some of the important issues that arise in dynamic social networks which result from social processes and other exogenous factors. We suggest a scheme as a way forward in understanding and analyzing such networks that change over time.

Keywords: agent-based social networks, dynamic social networks, evidence-based modeling

1 Introduction

The social network analysis community, in particular, those involved in organizational studies often have access to the data they are interested in. Especially, in case of the large business organizations, electronically archived data about e-mail correspondences, employee’s interaction activities, industrial liaisons etc., can be made available. Anthropologists too have been able to accumulate data through extensive fieldwork research, e.g. on kinship, social exchanges in rural and urban areas. The empirical data regarding fresh water management, land use change, rural migration etc. are however usually hard to acquire and are limitedly available. Applying social network analysis (SNA) in such situations is therefore very hard. An issue that then arises is the ‘boundary specification problem’ posed by Niklas Luhmann which refers to the task of specifying inclusion rules for actor or relations in a network study (Kossinets 2006). The point of concern [ibid] is that boundaries for links defined in models are usually arbitrary so it can be really hard to tell if the studied social network is indeed representative of the examined phenomena. As Edmonds and Chattoe (2005) ask, the difficulty lies in evaluating ‘how faithfully the standard network measures do characterise the network’. Excluding nodes and performing centrality measures a priori can lead to deception and in certain cases call for further evidence (Borgatti et al. 2006). The same problem arises when applying the SNA measures which theoretically assume that the network (or graph) is complete (Scott 2000). Even affiliation networks modeled represented as two-mode network structures, assume complete knowledge of actors and associated events (Wasserman and Faust 1994; Hanneman and Riddle 2005). This, incidentally, is ignored when the results are presented.
The *posteriori* approach used in applying graph-theoretic measures for network analysis has had successes in understanding static structures of the network. However, they do not help in understanding how such structures were formed. Merely identifying the centrality figures in the network, or the nature of information flow etc. does not explain the social interactions and the processes that produce them. To confirm one’s presumptions about the underlying phenomena, organizational researchers use either a whole set of measures such as centrality, cliques and their variants, or tend to apply rigorous analyses developed in other disciplines e.g. classical economics, statistical physics, game theory etc. Such analytic models though are mathematically elegant, often lead to over-simplification and thus lose further knowledge about the context of the network. Individual’s relations and actions are driven by their position and other factors affecting the system. Unlike physical systems or engineering domains, modeling social processes should be descriptive and evidence driven. Off-the-shelf methods cannot be used without understanding the underlying processes and the context.

Modeling social networks by agent-based social simulation (ABSS) methods addresses the issue of tackling complexity that arises as consequence to the interactions and the dynamics of the social entities. Some examples are Pujol *et al.* (2005) and Jager and Amblard (2005) etc. The techniques are better suited in giving the stakeholders and policy-makers further insight into the issues concerning the real world and to develop better policies accordingly. Agents are representation of social entities having local knowledge of the system and limited resources, and may influence each other’s action. (Ferber 1999). Social processes are both endogenous and exogenous. As Edmonds (1999) argues, ignoring an actor’s social relationships and their interplay in a model would not satisfactorily represent the actor’s behavior. This followed from Granovetter’s idea of social embeddedness (Granovetter 1985).

Whereas the SNA community and organization researchers do usually have access to the evidence, the social simulation community often does not. The simulation models thus rely mainly on the stylized facts and the knowledge they are able to acquire from domain experts. Validation on real evidence is therefore difficult on most cases though there are exceptions. An interesting case is the use of role-playing games in social simulation (Barretaeeau *et al.* 2001). This approach has a distinctive advantage in validating the model as the stakeholders are the best judge of a model’s behavior.

Agent-based Social Network (ABSN) models face a tougher challenge: characterizing co-evolution of the system as the simulation proceeds. Not only agents (abstract representations of social entities) are heterogeneous, their characteristics can change from what might have had been at the start. An easy solution would be to capture the ‘snapshot’ of the simulated network at regular time intervals. Such snapshots of the network could then be compared by SNA measures and other complex network characteristics, e.g. degree correlation, degree distribution, clustering coefficient etc. (Newman 2003). Stressing upon the concept of social embeddedness, Edmonds and Chattoe (2005) argue that an agent’s behavior cannot just be reduced to the notion of a mere node. That is, in complex systems it is very hard to anticipate the patterns that would emerge from interactions at the micro-level. Again, it would be misleading to apply measures on just the statistic snapshot of the network even though it was generated by dynamic processes.

Our present work leads to the study of the salient features of dynamic social networks and their validation through available social statistics and the qualitative narrative by the stakeholders. The case study is in the Limpopo Province in South Africa (CAVES 2005). The
model defines households as basic units and household clusters as extended-family structures. Other components of the model take care of the spread of HIV/AIDS in the community, creation/disintegration of households, role of grants, and formation of social clubs, etc. Social networks are modeled at the individual level where the agents’ have friends, and at the household level where the idea of a social neighborhood space is realized. The agents’ distribution varies during the simulation and so the ties change too. As the size and the structure can (and in our case, often) change abruptly and unpredictably at any time step, performing SNA measures for every simulation step may require extensive computational resources. Dynamic analysis of social networks claims to have overcome this problem by introducing process-oriented metrics and context-based performance metrics; e.g. (Tsvetovat and Carley 2005; Pujol et al. 2005) etc. The number of agents (or the number of nodes/vertices) in the network, however, remains same throughout the simulation. It becomes difficult when this number changes non-monotonically. Finding suitable measures to understand the dynamics of changing social networks and the underlying processes is therefore an open question.

The rest of the paper discusses the effect agents’ interactions may have on the network. The idea for identifying suitable measures based upon the context of the case-study is presented later in this paper.

2 Networks from Embedded Social Processes

Consider a simulated network \( S(N,E) \) at start, i.e. at time \( t=0 \). \( N \) is the set of nodes and \( E \) is the set of edges through which the nodes of the graph are connected. The agents are represented as nodes while the ties between them for the edges in the network. The network could be of any structure, e.g. unconnected \( (E = \{\Phi\}) \), small-world (Watts and Strogatz 2003), scale-free (Albert and Barabási 2002), random (Erdős and Rényi 1959) etc. At every time step, \( x \) new agents become member of \( V \), while \( y \) already present agents drop-off: \( x, y \in (0, \infty] \).

As \( N \) changes (or is likely to change) with each time step, the network changes too. Since the joining and pulling-out of the agents are driven by their socioeconomic conditions, they affect the agents’ decision. The distribution thus cannot be predicted in advance. The shape and size of the network at time \( t=t' \) could be radically different at time \( t'+\Delta t \) (where \( \Delta t \) is the possible time-lag of size ranging from 1, 2, … onwards; see Figure 1). It is possible that the network dissolves entirely after some time. Not only the size of the network changes, but also the degree may vary too, depending upon the type of relations the edges represent. In a nutshell, we have a graph that is changing at each time step. For the centrality measures, the number of nodes is the common denominator. Hence, it would be certainly deceptive to apply these measures at different time intervals and compare the statistics. For networks that evolve by
some algorithm monotonically, this is not a problem. The nodes represent the agents who form ties locally and under heterogeneous conditions. One needs a scheme that helps in understanding the interplay of the processes and remains robust to the changing network up to certain degree. Of course, in case the network degenerates, any such scheme is likely to fail.

With dynamic social networks modeling, one should avoid assuming any \textit{a priori} structure. We must not expect to end up with a specific formation either. For example, having a \textit{post hoc} assumption that the underlying social process would lead to a small-world effect or would show patterns of clustered volatility etc. is not suitable at all. The main reason is that it is the processes that generate network and not the other way round. It would be inappropriate to presume that the network(s) would take up the form of some characteristic network, e.g. power law etc.

Unlike physical systems, social processes are modeled descriptively and validated qualitatively. The evidence is gathered through fieldwork. An individual’s relations and actions are driven by their position and other factors affecting the system. Where the actions are constrained by both the endogenous and exogenous factors, one may find episodic volatility in the observed time series (Moss and Edmonds 2005). Catastrophic events, radical changes in the structure of the network may occur any time during the simulation. Hence the duration and magnitude of such activities cannot be predicted in advance.

3 Case Study: A South African Village Model

In a poverty-stricken region such as the rural sub-Sahara, poverty, food-insecurity, increasing number of deaths and other socio-economic stressors are concerns of much greater magnitude than the high prevalence of HIV/AIDS. In fact, HIV/AIDS not only affects the life of one simple patient, the entire household maybe ruined. This leads to the dissolution of affected households and in turns the entire community suffers if it fails to cope with the socio-economic stressors (Quinlan \textit{et al.} 2005).

To understand the social impact on households and the overall community structure, we choose the Limpopo region in South Africa, a case study in the CAVES Project (CAVES 2005). It is one of the most vulnerable regions lacking social infrastructure (Steinberg \textit{et al.} 2002; Ziervogel \textit{et al.} 2005). Many households have female heads because the men are often living away from the house for employment or have left the wife for other women. Grants in the Limpopo region are the primary source of income of which, a high percentage is spent on food, health and funeral costs. A major concern is the number of orphans in the community that has increased as a result of adult deaths of which HIV/AIDS is a major cause. Drought and lack of irrigation water, and little labour are coped mutually within the extended family and the neighbours. The extended family by and large accommodates dependents (orphans, old relatives) of a dissolved household.

External conditions too bound the modelling of social networks. Most important are the climate change (that affects land cover change and agriculture activities), policies for large scale investment projects such as water reservoirs, opening new job opportunities etc. and last but not the least public food security policies. With regards to social policy and its applications, the issues need to be tackled both at the national and the district levels. The former concerns with the implications for food and basic amenities subsidies for the local
districts. Authorities at the district level are often interested in the distribution of available resources to the village people and efforts towards sustainability of the households.

Pooling of finances, mutual help and resource-sharing among members are the basis of social networks in the community. Such networks are dynamic in the sense that existing households (or a cluster of households) disintegrate and new ones are created. Thus, relationships among the members of the networks change over time. The dynamics of the social networks result from the interplay of both exogenous and endogenous processes mentioned above. Alam et al. (2006a; 2006b) discuss the model structure and the implementation techniques in detail.

4 Social Processes and Networks in the Case Study

Human social systems could be represented at two levels: the individual (micro) and the collective (macro). Individuals interact with each other and form various ties depending upon their role and position in the system. As their socioeconomics status is dynamic in nature, the multiplexity of their relations in the system changes too. As Degene and Forsé (1999) quote Everett Rogers “Any given individual in a system is likely to contact certain other individuals, and to ignore many others.”

Social networks formed from social processes influence the individuals and the community at the two levels. According to Schillo et al. (2000), ‘modeling processes is to be located at the sociological micro level’. Social processes per se are intertwined and interdependent. A single individual contribution at the community level is fairly limited. Like any other complex system, actors’ interaction generate the aggregate patterns while their collective action constraints their behavior at the micro level. Many of the stressors, mentioned previously, directly affect an individual; e.g. an HIV patient’s health declines fast once the incubation period is passed. Death of a household head is likely to jeopardize the lives of the dependents. Likewise, drought, job losses, etc. affects an individual’s decision about crop plantation in their lands. Decisions to join different clubs or organizations (whether formal or informal) too are made at the individual level; the household head in our context. As reported by UNAIDS (2005), “In the hardest-hit countries, [HIV/AIDS] it is erasing decades of health, economic and social progress – reducing life expectancy by years, deepening poverty, and contributing to and exacerbating food shortages.”

At the individual level, we have agents as abstract representation of the village dwellers. They are born, age and die during the simulation. They decide to engage in farming on the basis of the climatic conditions. Some of them go for labor. Grants play a central role in the economy of the Limpopo region though very few are actually able to receive them. Several types of grants exist: disability grant, child/orphans grant and old age pension.

Anthropologically, households maybe classified as simple and ‘complex’. The former is the traditional nuclear household composed of a husband, wife and children. The so-called ‘complex’ household is defined as a household that contains a family in which there are two or more unmarried adults (or adult offspring) living together (Shah 1974). Such members might live separately later on. In our model, the simulation can be configured for both types as well as a combination of both (default setting). The household composition is an important measure in understanding the impact of the stressors. Orphans and disabled seniors are accommodated by next to kin households and sometimes by friends and neighbors.
Agents’ Friendship Network
Friendship and acquaintance play an important role, especially with regards to mutual help. Adult agents in the model are initialized with a certain (varying) number of friends with the upper limit, which is a parameter. It is dynamic in the sense that as the simulation progresses an agent’s friends’ list varies. Some friends may die and new friends are added over time. Currently, our model restricts to maintaining friends for adult agents (those with age > 15 years). As a child agent enters adulthood, they are assigned some friends. Moreover, social clubs gatherings and shared workplaces are also important niches for finding new friends.

Social Clubs
In our case study, we identified two social clubs for the start: funeral club/burial society and savings club (Radar 2005). Savings Clubs (or ‘stokvels’ in local language) are informal, localized groups common in the Sub-Saharan region (Ziervogel 2005; Verhoef 2001). The basic idea is quite simple. Each member of the group pays an agreed amount in a joint pool. The cumulative amount is then rotated to each member, e.g. by means of a draw. The savings club is modeled with two basic constraints: minimum number of members to form a club and the contribution, which is set fixed. The rotation goes on a monthly scale and the duration depends upon the number of members. We assign the roll for every member and they get the lump sum on their turn. From anecdotal account, we restrict the stokvels to be formed by female heads of the households. Some agents are ‘innovators’, i.e. they invite their friends and neighbors to join a stokvel and coordinate its working. It is quite possible that a member pulls out from the club due to death or that the household runs out of resources. Table 1 in the appendix illustrates the club’s mechanism.

Increasing number of deaths in the Sub-Saharan region is one of the major stressors that endanger the community structure. Death of an extended family member constitutes a financial burden and thus, many households belong to funeral clubs. These clubs provide money and other forms of aids to the bereaved families. In contrast to the informal stokvels, funeral clubs are usually institutionalized and may be receiving money from aid agencies, etc. Members also pay their respected monthly dues. The number of funeral clubs is a parameter in the model and are created with initial funds at the start. Table 2 in the appendix presents the current mechanism implemented for the funeral clubs.

Extended Family Network
While stokvels provide the opportunity to making new friends, funeral clubs are more associated to the extended family network. It is a very strong type of network in the region. As Ziervogel (2005) reports, relatives meet occasionally to discuss issues and socialize. Households who have no living adult left are accommodated by their nearest relatives. In our model, if the grandparents are alive, receiving pension and living in a different house, the orphans are moved to their place. According to Heuveline (2004), a major indicator in determining the impact of deaths caused by HIV/AIDS is when orphans are being accommodated by distant relatives or other households in the community.

Marriage patterns play an important role in the establishment of new households and kinship ties in the region (Heuveline et al. 2003). At this stage, the model randomly picks one adult male and a female from two different households and a married couple is formed. If the couple makes a separate household, they inherit the extended family links from the parent households.
**Household Social Neighbors**

We assume social links exist among households from start, which we identify as neighbors. There is no spatial neighborhood in the model. At the beginning of the simulation, we assign social links to the households (a small-world topology, by default). When it is not possible to accommodate them within the extended family, neighbors takes in the dependents. Currently, when a new household is created as a result of marriage, it inherits some of the social links from the parent households. Moreover, a household head may invite heads of the neighboring households to join a savings club.

### 5 (Some) Issues in Understanding Agent-based Social Networks

Affiliation networks represent the mapping of a set of actors to a set of events they maybe linked to (Wasserman and Faust 1999). Affiliation to different clubs or social circles of actors may either be overlapping or fully contained as shown in Figure 2. For instance, some agents may belong to the same savings club and be relatives at the same time. Since savings clubs are joined by household heads, the friendship and savings club membership relations could be both overlapping and embedded for different agents. One could speculate that there are no definitive boundaries between the micro and macro levels of abstraction. The extended family or social linkages is a relation that an entire household shares. At the individual level, they influence a household head’s decision to accept or refuse an invitation to join a savings or a funeral club.

![Figure 2: Embedded and overlapping affiliations](adapted from Degene and Forsé (1999))

One issue is using a common term for networks resulting from different relations at two levels. Several terms, e.g. multilayer, multilevel, hierarchical networks etc. have been used in different contexts. Ernst et al. (2006) call their social networks model as ‘multiplelayer’ which from the SNA perspective, can be perceived as a 2-mode network. A static 2-mode network could be represented, e.g. as a 2-mode sociomatrix, a hypergraph, a bipartite graph, and one representation can be mapped to another (Wasserman and Faust 1994). Traditionally, the metrics used in the analysis reduce them to 1-mode network analysis for finding density, rate of participation, connectedness etc.

Bipartite graphs are useful for simultaneous analysis of both actors and the affiliations. Besides the centrality measures etc. (Borgatti and Everett 1997), ‘complex networks’ counterparts for the bipartite graphs have been reported as well. Robins and Alexander (2004) demonstrate how 2-mode variants for calculating the clustering coefficients etc. could be used for a bipartite graph. However, as these measures rely on finding the appropriate denominator, we face the same problem as discussed in Section 2. Moreover, in case of fully-contained social groups, an interesting question is to ask if this property remains invariant in a dynamic network. Where events could be distinct, overlapping and/or fully-contained, we need to look for properties that remain conserved while the affiliations’ and actors’ sets change.
Hierarchical network is yet another term used for networks representing multiple relations. Freeman (1992) analyzed the two different notions of groups based on social affiliation. The first being ‘strictly transitive’ (Winship’s Model) and the second is Granovetter’s (1973) idea about the ‘strength of weak ties’. Winship’s idea of measuring social affiliation (or social proximity) to be a mapping from each ordered pair \((x, y)\) from a set of actors to real number \((0, 1)\) based on the ‘observable’ frequency of \(x\) meeting \(y\). Intransitive relations play an important role in knowledge diffusion in Granovetter’s model. Freeman’s approach for using hierarchical ordering (tree-like) is interesting for non-overlapping groups as individual members may ‘interact with outsiders’ as they would to those in their own groups. An important outcome of this formalism is that resulting cohesive groups form a hierarchical series and subgroups do not overlap except when one subgroup is fully contained in another.

On the other hand, the complex networks theory comes with its own suite of network measures. Most widely used is the average shortest path length which is the average of the shortest distance between every pairs of nodes. It is a typical network statistic to measure the network distance. However, in case when the network becomes fragmented due to loss of links or nodes, the average shortest path becomes infinity. As Ng and Efstathiou (2006) show, a resulting fragmentation can be calculated as the proportion of unreachable pairs compared to the theoretical maximum of a completely connected network.

Agent-based social simulations are usually analyzed based on a set of hypotheses. One way of testing the hypotheses is observing the time-series charts of ‘key’ performance measures. An important issue is the sensitivity of parameters as it requires excessive computational workload to explore the parameter-space. Another issue is representing the results as aggregates (e.g. mean, standard deviation, etc.) where the knowledge about the varying trajectories generated at different simulation runs are lost. Most agent-based simulation models of social networks remain content with a fixed number of agents.

Figure 3 illustrates the tradeoff in using simulation techniques for analyzing the dynamics of social networks. Observing the time series charts is usually insufficient to understand the underlying processes. The term ‘invariant’ is also deceiving in the context of simulation models, as situations change during the run. Observing the distribution generated from multiple runs of the simulation may help in guessing the system’s behavior. One may then identify measures and independent variables that remain valid in most runs. On the other hand, sticking to generalized analytic tools can facilitate in the analysis but at the cost of losing the description. It is therefore difficult in such a case to understand the factors that lead to certain patterns in the networks.

An important problem is how social processes constraint the dynamics of the generated networks at different levels. What is also worth investigating is whether and how the networks constraints agents’ decisions.\(^1\) This we briefly present in the context of our simulation model. However, we believe that it is possible to look for and/or construct social simulation models from various domains and show that this is indeed a property of the ABSN. Carley (2003) describes their notion of dynamic network analysis by means of a ‘meta-matrix’. So far we are unaware of any agent-based social simulation paper that has highlighted this characteristic of dynamic ABSN. We would appreciate if any such models or papers are brought to our knowledge.

\(^1\) This came under discussion with Richard Taylor following SJA’s talk at the Informal Manchester Complexity Seminar Series.
It is straightforward to think of situations where the social processes affect the generated networks. In our context, the tradition strong extended family system in the sub-Saharan region directly results in building ties among households. Social processes like marriage, even when there is no clear-cut pattern, not only results in a new household in the community; it also brings together households that might otherwise be unrelated at all. A household’s head decision to join a burial society is strongly influenced upon the memberships of other households in the extended family. On the other hand, the number and sizes of the savings clubs (Figure 4) in a community depends upon a household’s current economic status and its social links. A household’s dissolution and the accommodating of the dependents by their relatives affect the community’s social links. Orphans are typically accommodated by their nearest relatives. This ceases to hold when the nearest relative households are themselves on the verge of being disintegrated. In that case, the orphans are accommodated to other households in the extended family. As the accommodating household inherits whatever assets the dissolved household possessed, there is an incentive behind this decision. The topology of the community structure is thus affected.

Being represented at different levels and the respective networks constraints an individual’s decision and thus may affect the social processes on the whole. Starting from agents belonging to the same households, key decisions are usually taken by the household head. Friendship is a dynamic process in our model and an adult agent’s friends change over time. However, an agent’s friendship ties do not influence their joining a savings club unless they themselves become the head of their household. One way of determining the viability of a community structure could be the number of households and their size. A new household adds to the community network and builds new social ties with their neighbors. It is also an indicator that at least some couples in the community are able to build a house of their own. However, if there are job losses, or very high health expenses due to HIV/AIDS, couples would remain in their parent household and refrain from building a new one. Although this may be perceived as a good strategy to a common pool of resources, it may have drastic effects to the entire household later on. Increase in a household’s size is likely to result in further shortage of food and an increasing number of children left without care.

We have discussed specific scenarios from our model, in terms of social processes constraining the dynamics of generated networks and vice versa. Nevertheless, this important characteristic of ABSN can be identified in other evidence-driven models where assumptions are not merely justified for ‘simplicity sake’.
Suggesting A Way Forward

We propose to call our scheme as representing a two-level multi-relational network. An immediate question that arises is how this scheme addresses the ‘boundary-specification’ problem. Since we identify and attempt to model the activities of actors, the relations built upon the course of time produce the networks at different levels. The agent-based modeling approach is better suited for tackling this problem. Identifying agents’ decision procedures and then validating them qualitatively provides better credibility to the resulted networks. Missing one or several processes could significantly affect the simulation outcome. However, this provides the cue in adding further description, e.g. to the agent’s cognition, effects of the exogenous factors etc.

Figure 4: The circle layout networks represent the household social neighborhood. The random layouts (top) represent the networks at the individual level: the friendship network (left) and the savings clubs (right).

Figure 4 shows the ‘snapshot’ of networks at the individual level and the household level at some time \( t \) during the simulation run of our model. When the nodes and ties could change for each network (e.g. the household network on the left), just looking at one particular network may not be sufficient. Observing networks at the two levels can provide better insight to processes behind the networks. For example, looking at the savings club, the funeral clubs membership networks can explain the changing structure of the community at the household level. On the other hand, breaking up of the extended family network can help in explaining why a community structure dissolved after some time. Nevertheless, this idea maybe helpful only when the description entire simulation is recorded and a narrative account could be generated.

Key to identifying the processes that take place locally is the rule-based method. In our model, the social processes have been modeled declaratively (partially at the moment). The idea is to represent an agent’s cognition as rules. One can then keep track of the rules that are fired during the run (Werth et al. 2006). An advantage to this modeling approach is that one could look for the rules that would not fire after some time. For example, in case where the new households are not create any further, the community may no longer remain viable after some time. This might be the case due to high prevalence of HIV/AIDS in the village. As the factors that might result in extreme events gradually accumulate over time, they cannot be
predicted in advance. What one can achieve, however, is a better understanding of how the underlying social processes affect one another.

One can also look at the time series charts representing the ‘key’ processes. Instead of choosing these measures \textit{a priori}, observing the networks at the two levels can help in this regard depending upon the context. For example, one can then run the time series charts (Figure 5) for measures regarding availability of labor, households dissolutions, increasing number of orphans in the community etc.

![Figure 5: Time-series charts of some performance measures, and the households social neighborhood.](image)

7 Discussions and Some Related Work

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 \textit{a priori} set of hypotheses, which is even worse. A major obstacle is the possible unwillingness (for any reasons) of the stakeholders to feed-in the researchers. This is especially the case 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. 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 distinguishing features Schensul \textit{et al}. (1999).
A better way forward could be regular and more frequent interaction and feedback process to be established between the two parties. It is a good idea for the modellers to keep engaged with the fieldwork researchers, look at the problem with a breadth-first approach and develop their own general understanding. A rapid prototype model should then be developed and then proceed in parallel with continual evidence gathering by the case study team. A running prototype provides the case study team with the answers of what is to be supplied to the modellers.

Comparing two network snapshots at different time steps in the simulation would not help when the size, nodes and edges are most likely to change. Using centrality measures and geodesic distributions directly in this case would be inappropriate. Given the dynamic nature of the social systems, it is more helpful to move further from the traditional social network analysis techniques. Situations where the systems require representation at different levels of abstractions and the networks size varies, is hard to analyze. Analytic representations are elegant but involve risk of losing the context of the phenomenon under study. Evidence-based description of social processes should be modelled and validated qualitatively by the domain experts. As the social processes generate networks at different levels, network analysis measures need to be context-dependent. We believe, finding appropriate techniques for the problem posed in this paper is still an open research question.

One way of analyzing temporal change in the system is the ‘sampling’ of network diagrams at different time steps. Tsvetovat and Carley (2002) demonstrate this approach coupled with information flow and delegation of tasks during the simulation. However, much of the knowledge is lost, e.g. it is hard to answer questions such as, when, what triggered a certain change in the network structure at time (say) \( t=5000 \). Reynolds and Peng (2005) present their model for kinship networks, households comprise of husband, wife and children. Connections are built across households through marriages and both husband’s and wife’s parent-households are linked. They report results in terms of the number of cliques and other performance measures when the simulation ends. The household’s decision for looking for help relies on random, round-robin, etc. Another approach taken by the researchers is to use stochastic models. For example, van de Bunt et al. (1999) used a ‘random utility’ function to model friendship ties. Whether using probabilistic ties is ‘plausible’, needs to be debated at a greater length.

8 Conclusions

Social Networks are dealt with differently by the researchers typically depending upon their background and expertise. On one hand is the research community from the ‘complex networks’ looking for the (sub) structures and generative mechanisms of the networks. The idea is to understand the topological properties for networks from all sorts of domains. On the other hand is the community from the social network analysis who, having obtained the social networks data through fieldwork etc., are usually interested in the structural analysis of ties among actors etc. They have come up with their own set of centrality measures etc. over the years. With regards to the social simulation community, there is no doubt that there is a lack of analysis techniques for agent-based social networks. Mostly, the simulation outcomes are represented as time series charts of ‘performance measures’. This includes showing how e.g. the degree distributions may approach characteristic networks like small-world, power-law etc. Comparing simulation snapshots taken at time intervals and applying degree centrality and, diffusion measures etc. borrowed from traditional SNA are also employed.
The main purpose of this paper is to put forward the problem of analyzing ABSN when not only the degree distribution cannot be predicted in advance, but also the size of the network varies over time. This happens when the network size and relations is governed by the interplay of the social processes that constraints an agent’s behavior in the system. The complexity of the problem increases when such processes generate different networks at different levels of abstraction. For example, in the case-study discussed in this paper, there are ties built both at an individual’s level and at the household’s level. Social processes coupled with the environmental factors could drastically alter the structure at the macro level and vice versa.

We suggest that our agent-based simulation models should be evidence-driven and be more focused on the social processes of the underlying phenomenon. Sampling the network at time intervals would not help in a genuinely changing network structure. It seems that there does not exist any one way to perform the analysis and the techniques should be picked depending upon the context. It is certainly not helpful to constrain our simulation models by the analysis techniques we intend to use. For example, by always keeping the number of agents at least to a certain level etc. or making simplified assumption about the processes so as to come up with elegant analytic solutions.

Our model is still being developed and several other social processes need to be implemented. This is a work in progress and we expect further developments would to contribute to the understanding of dynamic social networks through bottom-up modeling approach.

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Appendix

Table 1: Pseudocode for the methods for creating and joining a savings club and the schedule

<table>
<thead>
<tr>
<th>Assumptions:</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Only women household heads join the savings club (stokvel).</td>
</tr>
<tr>
<td>II. Some agents are <em>innovators</em> ≤ MAX_INNOVATORS: having, e.g. able to stimulate creating a club etc.</td>
</tr>
</tbody>
</table>

**Savings Clubs (Stokvels) Creation Schedule:**
1. For all innovator ∈ Innovators | isHouseholdHead (innovator) ∧ joinClub (innovator)
   a. For each agent ∈ Agents | isHouseholdHead(agent) ∧ {innovator.Friend(agent) ∨ innovator.neighbor(agent)}
   b. sendInvitation(innovator, agent)
2. For each agent ∈ Agents | isHouseholdHead(agent)
   a. handleInvitation(sender); where sender is the innovator
   b. If (invitation-accepted) sendAcceptance(agent, sender); else sendRejection(agent, sender)
3. For each innovator ∈ Innovators |isHouseholdHead(innovator)
   If (#acceptances ≥ MIN_CLUB_SIZE) create new savings club

**handleInvitation:** on receiving the invitation from an innovator agent to join a new savings club
   If {(joinClub(innovator) ∧ !memberSavings) sendAcceptance; Else sendRejection

**joinClub:** a household head agent’s decision to join a savings club or not;
   If (household wealth ≥ SAVINGS_CLUB_FEE) join club

**Savings Club Rotation Schedule:**
1. For each member ∈ Members of the club
   a. If {isDead(member) ∨ isPulledOut(member) remove member
   b. If { not (|Members| ≥ MIN_CLUB_SIZE } finish club
   c. amount ← amount + member’s contribution
2. next candidate gets the lump sum amount

Table 2: Pseudocode for the methods related to the funeral clubs

<table>
<thead>
<tr>
<th>Joining and paying the contributions at a funeral club:</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. A Household joins when there is an adult bereavement due to HIV/AIDS; membership is permanent.</td>
</tr>
<tr>
<td>II. Dues (set fixed) are paid monthly. In case of consecutive default for ‘n’ months, aid is not given.</td>
</tr>
</tbody>
</table>

**Funeral Club Schedule:**
1. Receive request for payment from members.
2. If possible, pay all requesting members the funeral cost
   Else distribute the available funds equally.