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Dynamics of task oriented agent behaviour in multiple layer social networks

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The context of the model: Task oriented behaviour and a case study

In numerous real-world situations, people are confronted with tasks that they are unable to fulfil alone. Often, such tasks are characterised by the necessity to include a number of different expertises to their accomplishment. Consequently, people organise themselves into networks aimed at the completion of some specific task. Examples of such situations are to be found in virtually any domain, such as science, economy, or in the context of managing and maintaining natural resources.

The CAVES (Complexity, Agents, Volatility, Evidence, and Scale; see http://cfpm.org/caves/) project aims at describing the emergence, the characteristics and long-term behaviour of social networks of people using natural resources such as land or water. It is funded by the European Union and includes case studies in Great Britain, Poland, and South Africa to acquire data about real world evidence of social networks.

The Polish case study (with input provided by the Wrozlaw Institute of Technology and Wrozlaw University) focuses on those parts of the Odra river region that are at risk of regular flooding due to neglected or damaged dikes and the lack of maintenance of an old land reclamation system and also more generally on land use in the Odra river region. Social mobilisation or collective action by the individual farmers is required to maintain or re-establish the system of channels, ditches and dikes of the land reclamation system. Between the farmers, acquaintance or friendship links exist. When looking for collaborators to accomplish a maintenance related task however, the friendship network may serve as a starting point to build up a collaborator network, but the friendship network may not suffice to get all needed expertises together. By word of mouth, additional persons in the collaborator network (i.e. collaborators of collaborators) with the necessary expertise are sought, until the task can be solved. Such existing networks tend to be used again and again, thus leading to cliques of collaborators with complementary expertises.

In a more abstract way, situations like those just described can be characterised by the following features: They include multiple social networks representing multiple social contexts that interact, like friends vs. collaborators. People show goal or task-directed behaviour and use the networks at their disposition to fulfil their tasks. The conditions of the emergence of such multiple networks, their long term evolution, characteristics, interaction and their dynamics over time is of theoretical as well as practical interest to social science as well to complexity science. We will report on this dynamics by contrasting different social networks resulting from an agent-based model of task-oriented behaviour in a collective action situation. Specific measures have been designed to analyse the behavioural and structural efficiency of the networks and knowledge that is accumulated by the agents over time when solving tasks of varying difficulty.

Basic modelling concepts

In order to model the above mentioned situation characteristics, core features of the case study are abstracted. We follow a rather strict distinction between physical environment and social environment of the agents. This distinction focuses on a separation between physical and social spaces both in terms of semantics and techniques used for their representation. For various reasons, the simulation of the agent's physical environment uses a traditional grid based approach. The social "location" of an agent is given by his position within a social network context, where an agent is viewed as a node and social relations are represented by edges. Since agents are considered here in more than one social context an agent's social environment generally consists of more than one network layer. The modelled agents' perceptions vary related to their physical or social environment. Both perceptions are locally bounded in terms of a perceivable section of the surrounding physical space and in terms of network edges and neighbouring nodes (cf. Pujol, Flache, Delgado & Sangüesa, 2005). In the same way, the agents' repertoire of actions differs relating to their respective environment. In the model version presented in this paper, the focus is on the development of the social networks and the actions related to the natural or physical environment have been reduced to abstract tasks.

The agents' social environment is modelled as networks. An agent may be seen as a node in different social network contexts. Technically, an agent has slots that are nodes representing potential or actual social roles in different networks, so the networks actually resides in the agents' memory. Unlike in other network modelling approaches, agents do actively perceive their social environment and are enabled to act in their social network. In the model considered here, an agent has two semantically different nodes: One in an friendship or acquaintances network and one in an advisor or collaborator network.

The friendship network can be initialised with empirical data or in a more abstract way with an assumed small-world topology. A collaborator network does not exist initially. Once a task is assigned to an agent, it polls its social friendship network for expertise needed to accomplish the specific task additionally to its own. The search is started in the direct social neighbourhood of the agent. If the collected expertise provided by the network neighbour has been successfully applied, the agent builds up an edge to the respective node in the collaborator network. Next time the agent would first poll the collaborator context when looking for collaborators. If the agent cannot find all the necessary expertise in the directly neighbouring links of the collaborator network it will pursue the search in the neighbourhood of collaborators, i.e. collaborators of collaborators to find additional expertises.

In the following section, a description of the agent architecture that uses the described basic concepts will be given.

The SONATA model

The SONATA model (Social Networks of Abstract Task oriented Agents) has been realised in the RePast agent programming framework (http://repast.sourceforge.net). In order to describe the proposed agent architecture we follow the separation of the agent's functional components: perception, action repertoire and cognitive unit.

The perception unit generates information about the agent's physical and social environment. The perception of the physical environment provides local information about environmental attributes like resource availability, types of land cover, the locations of other agents, or in the more abstract version presented here, information about tasks and their accomplishment. The perceived social network environment is represented by lists of network neighbour nodes. Generally, these lists of nodes originate from multiple network layers. The agent "knows" about the semantics of each of those lists (as in the example above, it is known whether a network perception relates to the acquaintances network or the collaborator network). Perception is locally bounded, so no agent within the network has a global, bird's eye view of the whole network.

The action an agent may execute in its physical environment is to solve a task that has been assigned to it. To do so, it has to complement its own expertise by other expertises needed by looking for collaborators accordingly. Additional actions in the agent's social environment are network-related modifications like strengthening or weakening of outgoing and/or incoming edges, the establishment of new edges in already established networks.

The simulated social environment consists of two network layers. The friendship network the model starts with a pre-generated and stable small-world network with a given average node degree resulting from rewiring of a regular net according to the algorithm by Watts and Strogatz (1998). This network layer remains fixed over the whole simulation run. The second network layer is the collaborator network that builds up during the agent's search for supporters with specific expertises after being assigned a task. Thus, it is actively constructed by connecting to other agents that have already provided

the leading agent with useful information, following the algorithm described below. In this layer, unused edges slowly decay in strength and disappear once their weight becomes zero.
A task object is represented by a number of different kinds of expertise (know-how, expert knowledge) that is required to perform the task. Tasks are randomly assigned to agents and have a fixed difficulty which results from the expertise necessary to solve them. Expertises are evenly distributed among the agents. Each time step, one agent is assigned with a task for which he needs the expertise of other agents. It will utilise its social environment to compile the required expertise to accomplish the assigned task. An agents first polls its collaborator network to get help from agents that have previously been helpful. If it cannot find enough collaborators among its direct ties, it is able to contact direct collaborators of its collaborators. It will build up edges in the collaborator network to these agents if they supply it with the necessary expertise. Only in the event that polling the collaborator network does not yield the necessary expertise, the agent will use its friendship network. If an expertise looked for can be got from a network neighbour, the agent will build a new network edge in the collaborator context to the supplier of the expertise.

Results
In this paper, we will compare scenarios where only the initiator of the task builds up arcs to his collaborators (scenario without pairwise linking) with scenarios where all the agents that took part in the task build up arcs to every one of the participating agents (i.e. with pairwise linking). In both scenarios the agents have a maximum in- and out-degree, i.e., they are able to build or receive a limited number of arcs. Special attention will be given to the behavioural efficiency in solving tasks and the structural efficiency (i.e. number of links that are built up). All analyses of the networks generated by the RePast model have been done with the Pajek network analysis tool (de Nooy, Mrvar, & Batagelj, 2004) and R, a free software environment for statistical computing and graphics (http://www.r-project.org/), with methods also discussed by Newman (2003) and Wasserman and Faust (1994).
All the networks discussed here have been produced with the following model parameters: There are 100 agents. The average degree in the (static) friendship network is set to 20. There are 10 expertises needed to solve a task. Accordingly, the maximum degree for the collaborators is set to 9, relating to the number of additional expertises (beside the one the agent possesses). Every time step, 1% of the agents are randomly assigned a task. All agents are cooperative in the sense that they do not turn down a request for joining a task solving group (except if they have reached the maximum in- or out-degree or if they are already engaged in a task). Links decay over time and disappear after 150 time steps, unless noted otherwise. The simulation stops after 100,000 time steps.

(a) Collaboration networks with and without pairwise linking: Stability and task completion efficiency
Figure 1 shows the comparison of three types of collaboration networks with regard to the number of edges added in each time step (as a measure of re-linking activity), the number of tasks successfully completed (a measure of efficiency), and the average out degree of nodes (reflecting the connectivity of agents). The three networks differ with regard to their decay of links and to the knowledge that is gained from a successful collaboration. In one type of network, only the agent having been assigned the task builds up an arc to its collaborators (networks without pairwise linking). Collaborators thus do not necessarily know each other after solving a task. In the other (and more realistic) network type, successful collaborators establish reciprocal links to each other (nets with pairwise linking).
The upper graph of the number of edges added shows that both the network with no link decay at all and the one with pairwise linking soon reach a high degree of stability, whereas in the network with decay and without pairwise linking, a constant high activity of adding new links can be seen. To solve tasks successfully in this network, new links have to be added constantly, countering the forgetting process.
The middle graph, depicting the number of tasks successfully completed, shows how two of the networks reach a perfect degree of task completion after a certain time whereas the net with decay and without pairwise linking only reaches a (highly varying) degree of about 80% of the tasks completed. Pairwise linking seems to foster stability and successful task completion as well as a perfect agent memory.

The bottom connectivity graph shows the reason for the imperfect task completion in the network with decay and no pairwise linking. It does not reach the level of connectivity necessary to “be ready” when the task is assigned.

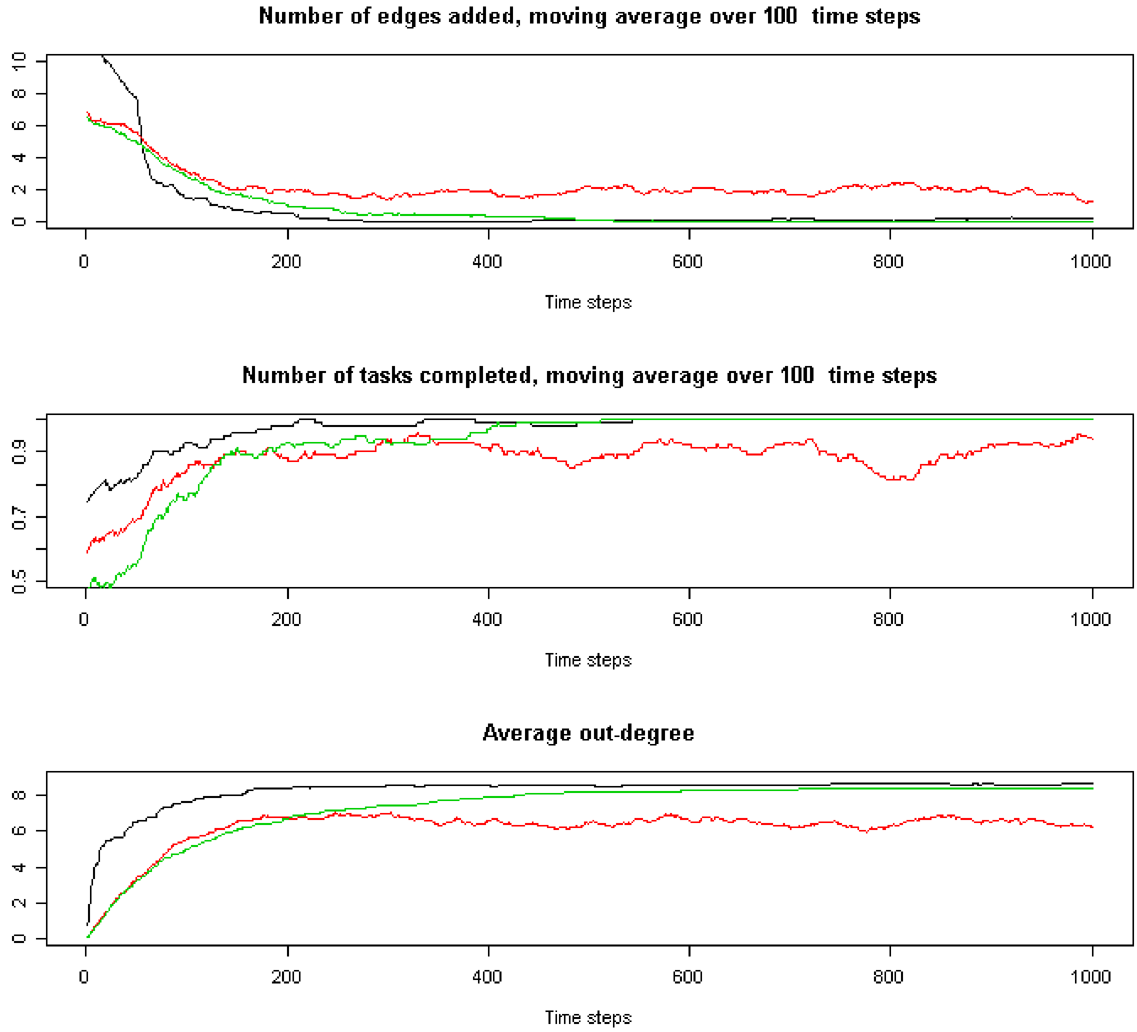

Figure 1: Number of edges added in each time step (top), number of tasks completed (middle), and average out degree of nodes (bottom) in three different SONATA collaboration networks: One with no decay of links and without pairwise linking (green lines), one with a decay of 150 time steps and also without pairwise linking (red lines), and a network with a decay of 150 time steps and pairwise linking (black lines).

Figure 2 digs somewhat deeper. In these charts the frequencies in which edges are used in the collaborator networks under different edge decay rates are examined. This variable is negatively correlated to the creation of new edges: Only stable links can accumulate a higher number of uses over time. The three rows show networks without pairwise linking and with decay rates of 300, 600, and 900 respectively. Horizontally one can compare the frequencies of edge use at different points in time under the same edge decay rate. Vertically, one can compare the frequencies at the same point of the simulation under different edge decay rates. The network with a decay rate of 900 stabilises soon: Edges once built up are used repeatedly. The use is distributed approximately normally among edges. The first row with edges decaying after 300 time steps in contrast show no stability being reached. Links decay before they reach a high age and have to be reconstructed throughout the whole simulation. In the middle row, we see some edges stabilising and some not.

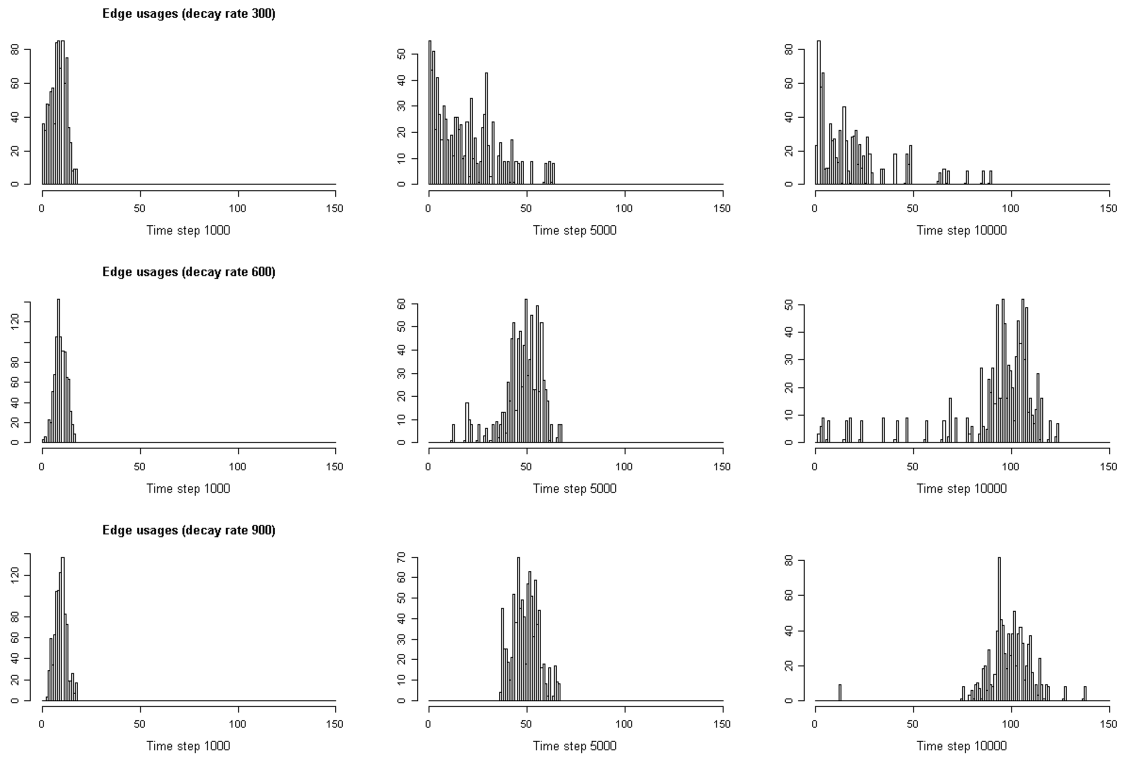

Figure 2: Histograms of the frequency distribution of edge usage in SONATA collaboration networks without pairwise linking with different edge decay rates. The X-Axis displays the number of times edges were used, Y-Axis shows the number of edges. The histograms each show the number of edges used with a certain frequency in snapshots after 1000, 5000, and 10,000 time steps (horizontally). The top row shows results for a decay rate of 300, the middle row for a decay rate of 600, and the bottom row for a decay of 900.

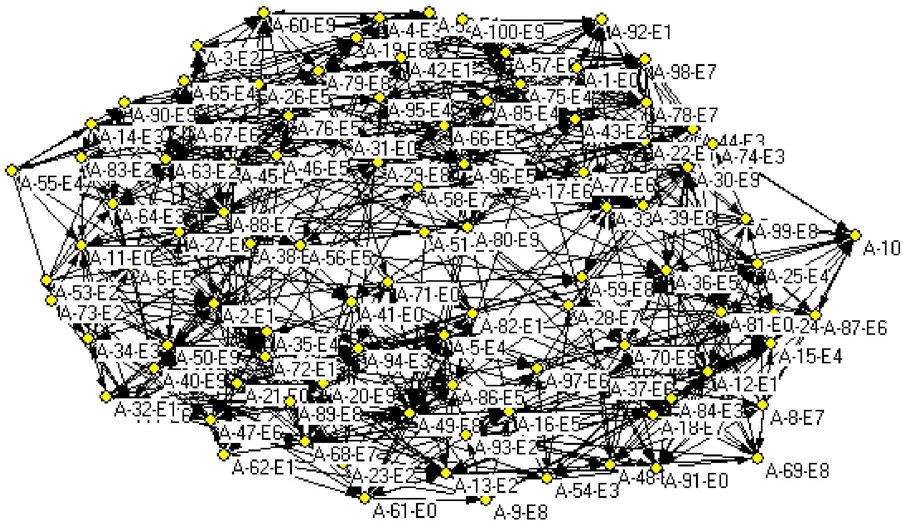

Figure 3: Collaborator network after 40,000 time steps in the scenario where only the initiator builds up an edge to its collaborators (i.e. without pairwise linking). Decay of edges is 150 time steps. This network has a very low clustering coefficient of 0.19.

Figure 3 shows a network with no pairwise linking and with a decay of 150 after 40,000 time steps, i.e. after a very long running time. The agents are interconnected relatively loosely in one cluster. This is the network structure that relates to the low task completion efficiency depicted in figure 1 (red line).

(b) Very long term evolution of social networks: The emergence of collaboration cliques

It is interesting to follow the structure emerging from the task assignment and pairwise agent linking algorithm over time. Figure 4 illustrates the typical network structure after 10,000 time steps. Clustering can be seen to start. Therefore an agent who is situated in such a tightly connected cluster does not need to find suitable collaborators in the friendship network or via collaborators of collaborators.

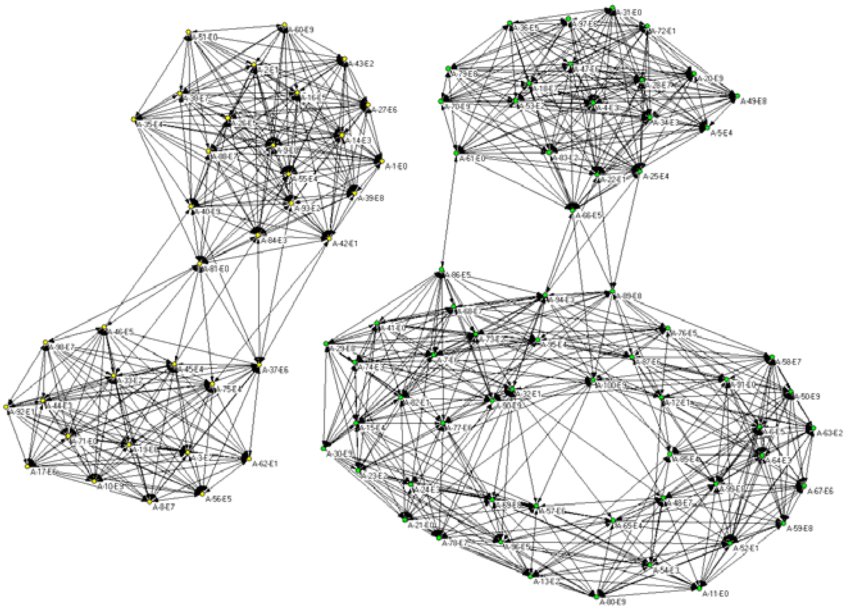

Figure 4: Collaborator network with 100 agents ('A-1' - 'A-100') with 10 different expertises ('E-1' - 'E-10') and a maximum in- and out-degree of 9, after 10,000 time steps. At this point of the simulation agents with different expertises start to gather into (task oriented) cliques. This network has a clustering coefficient of 0.68.

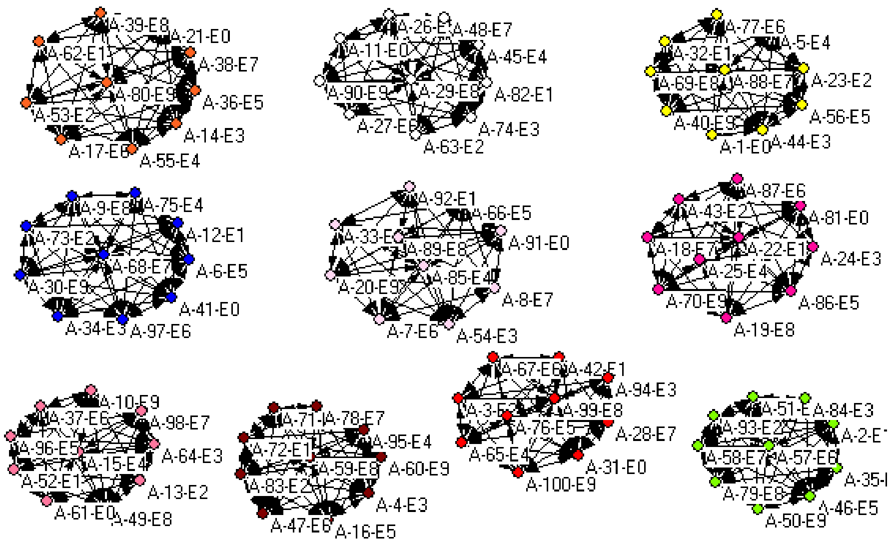

Figure 5: The same collaboration network after 80,000 time steps. All agents have separated into tightly clustered components where they have exactly the nine collaborators needed for their task. No more new edges need to be added. The clustering coefficient of this network is 1. That means that all neighbours of any agent are adjacent to one another.

Figure 5 finally shows the network from figure 4 after a running time of 80,000 time steps. On one hand, it has reached stability and highest task completion efficiency. On the other hand, it has separated into 10 cliques of 10 agents that have no more connection between each other in the collaborator (but still in their fixed acquaintances) network.

Discussion

This paper has presented a model of the emergence of task oriented or collaboration networks from an acquaintance network. This matches in an abstract way many real-world situations where such a collaborator network has to develop on the basis of the social relations that already exist, once some task arises.

The results of the SONATA model show how a forgetting rate higher than the rate of new tasks coming in causes established links to disappear, so that the collaboration network has to be built repeatedly. The structure of the network thus never stabilises, and efficient cliques never emerge.

Stability of network links also depend crucially on the way of linking: If, after having completed a task successfully, all participating agents link to each other in both directions (pairwise linking), stable structures arise that can be used again as soon the next task is assigned to one of the cluster's members. This can be interpreted as groups remembering the good work they did together and whom they did it with. These pairwise linked networks thus accumulate with each task completed a maximum degree of knowledge relating to possible future collaborators. The knowledge is distributed evenly among collaborators and does not reside only in the agent the task was originally assigned to (no pairwise linking).

The higher efficiency of pairwise linked networks is reflected in a higher degree of tasks successfully completed and a higher degree of connectivity, but it has one drawback. Long-term evolution of such networks shows a segregation of successful cliques over time. While this may be well adapted to the task structure used here (with a constant amount of 10 expertises needed), this system may break down if there are substantial fluctuations in the quality of those tasks. Since the tasks assigned are the abstraction of the problems posed by a natural environment, this may be an important consideration. It will be investigated how shocks on the system, e.g. by changing the task structure, affect the networks with regard to their structure and performance. What does the system need to adapt to new situations? How long does it take to stabilise again, if ever?

With further empirical data from the Polish case study, measures of the actual social networks in the Odra region will be compared with the simulated ones on a qualitative level to validate the emergent network structures. To that aim, we will be incorporating data about networks and physical evidence (about geography and land use) from the Polish case study into the coarse grained SONATA model described in this paper. This will also lead to the random assignment of tasks being replaced by more realistic assumptions about the actual processes included in the maintenance of the land reclamation system. The friendship network layer has been fixed over the whole simulation run in the model presented. This static view has also to be replaced by a dynamic representation that takes into account aspects of a (possibly fluctuating) physical neighbourhood and aspects of growth and shrinking due to fluctuations in the absolute number of nodes (cf. Jin, Girvan, & Newman, 2001). Also, expertise is not distributed evenly in real world situations. In future scenarios, the effect of unevenly distributed expertises will have to be investigated. The emergence of scale-free nets under this scenario seems possible. Agents that possess a rare expertise will potentially function as hubs (Albert & Barabási, 2002).

One very important aspect is still missing in the model presented here. There are no positive or negative consequences for the agents if they succeed in performing the tasks or not. There is no economic effect of actions in the physical environment, like the task of maintaining land-reclamation systems is directly related to the physical environment. The structure of the land-reclamation system is that of a collective action (Olson, 1965) or of a social dilemma (Dawes, 1980). To simulate a collective action, there will be a positive payoff if the task has been successfully completed, i.e., if enough agents with the necessary expertise will have participated. But before participating, each agent will have to pay an amount of resources (money, time). The resulting payoff will not be received by the agents but will increase the value of the arable land where the agents executed the assigned task (reflecting the land quality gain by the reclamation system). Agents who live in the vicinity of the land parcels where the task was successfully executed will also profit from the maintenance of the land-reclamation system, even if they did not participate in the task. Agents therefore have an incentive not to participate in a time and money consuming task but to profit from the work of other agents. However, if the necessary number of expertises is not reached, no task will be completed and no positive payoff from the environment will result. The participating agents will have invested money and time without profiting from their work.

To deal with the growing complexity of decisions agents face in more multifaceted physical and social situations, rule based decision making mechanisms will be integrated into the SONATA architecture to allow for incorporating more complex, yet modular knowledge structures.

References

Albert, R. and Barabási, A.L. (2002): Statistical mechanics of complex networks. *Rev. Mod. Phys., 74*, 47–97.

Dawes, R.M. (1980). Social dilemmas. *Annual Review of Psychology, 31*, 169-193.

Jin, E., Girvan, M. & Newman, M.E.J. (2001). The structure of growing social networks, *Phys. Rev. E 64*, 046132 .

Newman, M.E.J. (2003). The structure and function of complex networks. *SIAM Review, 45(2)*, 167–256.

de Nooy, W., Mrvar, A. and Batagelj, V. (2004): *Exploratory Social Network Analysis with Pajek*. Cambridge University Press (Cambridge).

Olson, M. (1965). *The logic of collective action.* Cambridge, MA: Harvard University Press.

Pujol, J.M., Flache, A., Delgado, J. & Sangüesa, R. (2005). How can Social Networks Ever Become Complex? Modelling the Emergence of Complex Networks from Local Social Exchanges. *Journal of Artificial Societies and Social Simulation, 8* (4).

Wassermann, S. & Faust K. (1994). *Social Network Analysis*. Cambridge: Cambridge University Press.

Watts, D. & Strogatz, S. (1998). Collective dynamics of small-world networks, *Nature, 393*, 440 (1998).