Self-organising processes of task allocation

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Chapter 2
Modelling[2]

Abstract
In literature, self-organising social behaviour is often described by means of a brain metaphor. These descriptions either discuss some general principles or propose a systems-theoretical analysis, but have not been related to existing psychological theory. In this chapter we propose a way of describing self-organising social processes of task allocation by using principles derived from a neural-network model and from theories of cognitive- and social psychology.

2.1 Introduction

Unlike other animal behaviour, human behaviour is embedded in an institutionalised context. If we want food, we do not hunt, but go to a store, pay money that we earned doing a job we once applied for in an organisation. In our spare time we are part of another structure, playing sports, taking some courses, or watching television. Even our holidays may take a pre-structured shape, e.g., visiting a holiday-bungalow or trailer vacation park we are visiting for the 25th time. In some cases, humans can be considered as institutionalised animals. Usually the institutionalisation of human behaviour seems an efficient way of organising large groups of people. It is safe and it is easy. But in some cases, safe and easy may become boring and rigid. In these cases the human animal becomes a caged pet of the society that once emerged from his own behaviour. In a 'healthy' society, institution and individual freedom should be well balanced. Life without structure leads to chaos and structure without freedom implies inhuman conditions. This balance does not only yield for society but reflects a general principle regarding order and chaos in living systems (Ashby, 1956; see also Kauffman, 1995).

In this chapter, we will not present some general considerations about order and chaos in relation to living systems. We do not even want to discuss the implications for society. We only shall deal with the question how organisational behaviour is related to the principle we just mentioned. This means that we want to answer questions

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regarding the relation between the order of an organisation and the chaos of its environment. According to Ashby's law of requisite variety, the internal diversity of any self-regulating system must match the variety and complexity of its environment if it is to deal with the challenges posed by that environment. (Morgan, 1986, p. 100, after Ashby, 1956). One of the questions this law may answer is whether employees should specialise in one particular skill or perform all of the necessary skills to perform a task. This particular type of question, which refers to principles regarding specialisation versus generalisation, should be considered the main issue of this chapter. One of the implications of Ashby's law is that there is an optimal organisation for every task. Molleman (1998) discussed the implication of Ashby's law for organisational design more elaborately. He states that if the level of task variety is low, standardisation will be the most efficient and effective. If the level of variety is high, the assignment of control tasks to the individual worker will fit in best. If the level of variety is moderate, autonomous teams will give the best result.

However, the proposed relation between task variety and need for organisational structure is merely static and design-based. In practice the environment is constantly changing, task variety itself being an altering component. This suggests that, for a complete understanding of the relation between task and organisation we should study the processes of organising and learning as well. This means we have to answer the question: how do people organise themselves according to a task they must perform? This question refers to human behaviour as self-organising instead of simply following an existing institution. The study of self-organising social processes has two main purposes. First, insight in adaptation processes regarding task alterations may provide a practical use in organisational settings. Second, studying the relation between tasks and organising behaviour does not refer to human behaviour as an institutionalised animal, but as an animal that can create institutions. We can only answer the question to what extent we need organisational structures if we know what our behaviour is like without them.

This brings us to the question of the best approach to follow. The study of self-organising behaviour without an organisational context may need an experimental setting, such as at team-building sessions and the like. However, for a number of theoretical and methodological reasons, within social psychology, experimental studies of organising behaviour in particular and social dynamics in general cannot build on an extensive tradition (Vallacher & Nowak, 1994). Computer simulation introduces the possibility of a new way of thinking about social processes, based on ideas about the emergence of complex behaviour from relatively simple activities (Gilbert & Troitzsch, 1999). The idea of the emergence of complex behaviour from simple activities can be found in the area of cognitive psychology as well, such as Searle's description of consciousness as the final result of properties that emerged from simple neural activities (Searle, 1992). But this is not the only similarity between studies of social dynamics and of the brain. Both can be described as self-organising systems. This notion is not new. Some scholars used the metaphor of the brain, being the most widespread known self-organising system, to describe social behaviour as well (e.g. Beer, 1981; Morgan, 1986). However, these descriptions do not reflect common theories of social psychology.

Both similarities, the notion of emergent properties and the notion of self-organisation, form the basis for the model we propose. In the first part of the chapter we will discuss the use of a brain metaphor for describing self-organising social processes. As we shall point out, by using a self-organising neural network model, being a particular model of the brain, we shall integrate different social psychological theories and models into a theoretical framework. The theoretical framework itself is a multi-agent architecture. We shall describe this architecture at two levels, the skill-level and the individual level. At the skill level, we shall describe the cognitive architecture of the single agent. The social level deals with the interaction between agents.

2.2 Neural Networks and Social Processes

In this section we describe some general principles of self-organising neural network models. A self-organising system can be considered as a system that can change its own structure. A neural network is a set of interconnected nodes with an excitation level that serves as a model of the structural architecture of the brain (for an overview, see Rumelhart, Hinton, & Williams, 1986; Smolensky, 1986). Principles of neural networks will be related to existing psychological theories and models to describe social processes of task allocation.

2.2.1 From a brain metaphor to self-organising neural networks

Self-organisation refers to the process in a system leading to the emergence of global order within this system without the presence of another system dictating this order (e.g. Dalenoort, 1989; 1995; Heylighen, 1997). Self-organising systems have been object of study in a wide variety of disciplines, such as chemistry (Prigogine & Stengers, 1984), biology (Maturana & Varela, 1980) and cognitive psychology (Dalenoort, 1982; 1995). Self-organising principles of social systems have been formulated as well (for an overview, see Ulrich & Probst, 1984) but those principles are formulated in an abstract system-theoretical way and are not related to social psychological theory. Some scholars use a 'brain metaphor' for describing self-organising social behaviour (e.g. Beer, 1981; Morgan 1986), or discuss the use of neural networks for describing social processes (Ritschard, 1991; Zoethout, 1994).

Indeed, we could mention at least three arguments to use a brain-metaphor for describing social behaviour with respect to learning. First, in the area of artificial intelligence, neural networks are widely used because of their ability to learn. A model that describes social behaviour based on neural-network-like properties should also be capable to describe learning processes in social systems. Second, the brain is the most commonly known self-organising system. The use of a brain-like description opens the possibility of using knowledge regarding self-organising behaviour to describe social systems. Third, neural networks are used to describe complex behaviour by means of simple interconnected elements. On the basis of the interaction between these elements, properties are likely to emerge that cannot be attributed to the individual elements (Dalenoort, 1982; Heylighen, 1997). The notion of 'emergent properties' can be used to describe complex social processes resulting from individual behaviour as well (Gilbert & Troitzsch, 1999).

Some of these arguments concern with the use of the brain-metaphor in general; others regard the self-organising neural-network model in particular. Self-organising neural-network models are biologically plausible models of the brain. The brain is able to adapt to the environment autonomously by changing its own structure accordingly. Therefore the brain can be considered as a self-organising system. Furthermore, these self-organising processes may lead to more efficiency, which indicates that in fact the brain is a learning system (Krippendorf, 1986).

2.2.2 A neural-network model: properties and principles

The main scope of the chapter is self-organising social processes of task allocation. Therefore we shall only mention the neural network properties that we will use to describe these processes.

A neural network consists of a set of interconnected cells with an excitation level and a threshold. Within these cells the excitation level is built up until it exceeds the threshold. If the excitation level exceeds the threshold, the cell fires to the cells connected. The excitation level of these connected cells changes as a result of this (Dalenoort, 1982). We may discern two types of connections: excitatory and inhibitory: an excitatory connection increases the tension of the connected cells and an inhibitory connection decreases the tension. Connections may vary in strength: if a connection is stronger, the proportion of excitation or inhibition is larger.

Since the brain is self-organising, there is not a mind that dictates its order. The brain creates its own order and changes its own structure autonomously. This implies that a description of the way the brain changes its own structure should be based on interaction principles of the elements (i.e. neurons) the brain consists of. In the literature a mechanism that describes this interaction is 'Hebb's learning rule'. It implies that for the emergence of a new connection between two neurons, or for strengthening an existing connection, these neurons must be active simultaneously (Hebb, 1949). This mechanism is not only the only mechanism that describes processes of self-organisation and learning within the brain, it can be considered as a general learning mechanism as well, that can be used to describe learning processes in other self-organising systems. Therefore Hebb's learning rule can also be used for social systems (Zoethout, 1994; Nowak, Vallacher, & Burnstein, 1998; Kitts, Macy, & Flache, 1999).

Another obvious but nonetheless important similarity between the brain and social groups is that both are living systems. Living systems can grow tired: in a neural network model neural fatigue might be due to an overall ability to reach sufficiently high levels of excitation (e.g. can be described as a tension decrease of afferent cells after a longer period of firing. We can experience this in a train: in a travelling train, the constant input of the rails passing by leads to a decrease of the excitation level of the neurons. At the railway station this results in the experience that, as soon as the train has stopped, we notice that we are going backwards instead of standing still.

2.2.3 Social processes of task allocation

Now we relate the properties we discussed above to the self-organising social processes of task allocation. Social processes of task allocation refer to the way people allocate tasks they should perform together. For instance, a group hiring a sailing boat should perform (at least) the following tasks: handling the helm, the jib, the sail, the swords, looking at the weather, watching the environment, and monitoring the rest of the crew. The crew should decide who does what. This decision may depend on the skills of the individual crew-members, their willingness of performing either one of these skills, the power and experience of the captain, and the 'degrees of freedom', the space in which the process of allocation may take place: if the boat is small and consists of only one crew-member we do not have to think of social processes of task allocation. Furthermore the captain of a professional sailing ship that is participating in a contest may have carefully selected his crew of highly skilled specialists. In neither of these cases we speak of self-organising social processes of task allocation. In the first case there are no social processes and in the second case there is no self-organisation. We stated that a self-organising system refers to a system that can change its own structure. This means that we want to describe situations in which the process of allocation occurs inside the system. On board, a crew of three people should autonomously decide how to use their skills in a smart way. This may finally result in a crew of well-trained sailors, balancing between specialisation and multi-functionality. What yields for the sailing boat may also apply to daily working life: a group of people plucking apples, making cars, performing surgery, doing their jobs is somehow involved in allocation processes. This brings us to the question which components influence processes of task allocation. In order to answer this question we should distinguish between task components and psychological components.

2.3 Task Components

Much research has been devoted to the area of tasks, task allocation, and designing organisations to perform tasks as effectively and efficiently as possible (for an overview, see Hunt, 1976; Steiner, 1972; see also Tschan & von Cranach, 1996). Wood (1986) describes three dimensions of task complexity: Component complexity describes the number of different actions necessary to perform a task. This resembles the dimension of skill variety of the Job Characteristics Model, a model that is widely used in work and organisational psychology (Hackman & Oldham, 1980). Every task can be split up into actions in such a way that every action needs exactly one skill. Co-ordinate complexity refers to the extent to which the different actions are connected. This is also called task interdependence (Thompson, 1967; Van der Vegt, Emans & Van der Vliert 1998). Dynamic complexity refers to the task changing in time (Tschan & von Cranach, 1996). This is also called task variety. As task variety increases, the task itself becomes less familiar, which implies that the information about the task decreases. In literature, the information about the task is often referred to as task uncertainty (Manz, 1992; Molleman, 2000). According to this description, a task can be defined as a set of actions, in such a way that every action requires one skill to perform it (see Figure 1):

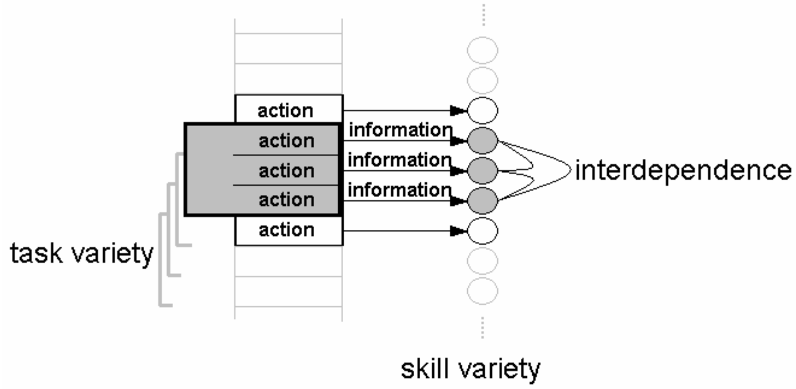

Figure 1: Components of task complexity

In the figure, the actions required to perform a task are represented as a grey box. The component of task variety (e.g. dynamic complexity) indicates the variety of actions. Every action sends out information about what must be done. This information activates the skill that is necessary to perform the action. In the figure the activated skills are represented by the grey dots. High task variety implies low information (e.g. high task uncertainty) about the actions. As the actions a task consists of increases, more skills are necessary to perform the task. This is called skill variety (e.g. component complexity). Interdependence being a task characteristic refers to the relations between the different actions a task consists of. Some actions may be conditional for others; some actions may be inseparably connected. These relations imply relations between skills as well. This refers to the situation in which the agents are forced to co-operate because individually they can only contribute partly to the performance of the task. In the next section we shall describe people as agents with a set of skills. This description indicates that if this set of skills is not sufficient to perform a task on its own the agents should work together.

2.4 Psychological Components

In psychological literature, human behaviour is often described as using two dimensions, for instance: task-directed and social-emotional, goal-directed and sensation-seeking (Apter, 1987), the need for certainty and the need for pleasure (Veen & Wilke, 1986), or love-hate and dominance-submission (Leary, 1957). These dimensions can be found in studies on task performance in groups as well. Wilke and Meertens (1994) state that the most important components that determine performance are: expertise, motivation, and co-ordination costs. Expertise and motivation can be considered as characteristics of skills: some skills are performed better than others (expertise) whereas some skills are more preferable than others (motivation). Co-ordination costs can be considered to be dependent on the interaction between individuals, i.e. social interaction. Social interaction can be described in two dimensions as well, for instance power-submission and love-hate (e.g. Leary, 1957).

Thus task performance can be described at the skill level by means of two components, expertise and motivation. At the individual level, we use the components power and attraction.

The components Wilke & Meertens (1994) proposed, as well as the use of two dimensions to describe human behaviour, will form the basis notion of a multi–agent architecture. This architecture relates psychological theory as well as the neural-network model to both the skill-level and the individual level.

2.4.1 The cognitive architecture of the agent

We have defined a task as a set of actions, and a skill as the ability that is required to perform one action. This means that every action of a task requires the matching skill to be performed. We describe a skill by using two components, motivation and expertise (derived from Wilke & Meertens, 1994). In analogy to the neurons in a neural network, every skill can be active or passive. A skill is activated if it is necessary for performing a task. In order words, a task will activate the accompanying skills. Information about the necessity of the skill will determine the level of the activity.

The activity of the skill represents the motivation of using this skill. Some skills, such as handling the helm in a sailing boat, are nice to do. Others, such as pulling the swords, or the jib are less motivating. On the one hand our motivation to use a skill increases if we would receive more information regarding the necessity of this skill: it is nice to know why we must do something. On the other hand, if the same skill should be used over and over again, we eventually would know the skill so well that it could be boring to use it. This inverse relation between motivation and information is the most important reason for the failure of Taylor's scientific management (Taylor, 1911). Using the neural-network analogy, we describe motivational decrease as a result of 'neural fatigue'.

Motivation is one of the components a skill consists of and by itself insufficient to perform a task. We may know that we should handle the helm and we even may be very motivated to prevent the ship from colliding with the shore. But this will not necessarily imply we know how to handle it properly. Expertise refers to knowing how to use a skill. Expertise increases the more often a skill is used, and it will decrease if it is not used for a longer period of time. In analogy to the neural network model we shall represent the expertise of a skill as a connection between 'skill' and 'use of skill'. In this way we are able to describe changes in expertise by means of Hebb's learning rule: expertise increases as the activation of a skill and the use of a skill occur together frequently.

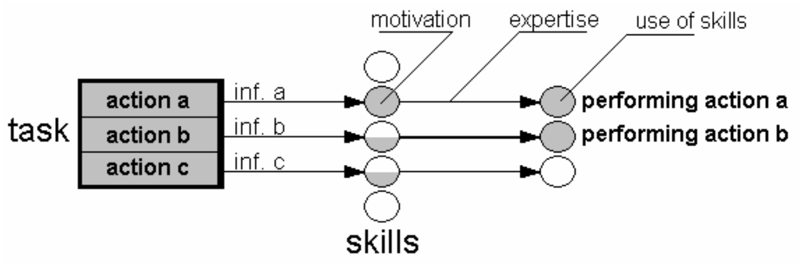

Figure 2: The representation of the relation between a task, skills, motivation, and expertise

Figure 2 explicates what we have described so far. In this example a task consists of three actions. Here we will use the example of John and his sailing ship. The task is ‘sailing’, action a is ‘handling the helm’, action b is ‘handling the sails’, and action c is ‘watching the other ships’. John has low expertise in handling the helm (in Figure 2 represented by the thin arrow between skill a and ‘ use of skill a’) but he is very motivated to use this expertise (skill a is completely grey, i.e. highly activated). Furthermore John has high expertise in handling the sails (in the figure represented by the thicker arrow connecting skill b with ‘use of skill b’), but he not very motivated to do it (in the figure represented as the dot that is 'half-grey'). However, until now, John has never sailed alone before. This means that he knows something about the other ships and traffic rules, but he does not know how to use these rules, and he does not feel motivated to apply them either! Thus, John decides not to go sailing by himself.

The skills to perform a task, and the components a skill consists of, i.e. expertise and motivation, are embedded in a cognitive architecture. Every agent has a set of skills. The activity of skills can be described in the same way we can describe memory. Memory consists of Long-Term Memory (LTM) and Short-Term Memory (STM). LTM is the part in which all of the skills and accompanying components exist passively. As we stated, as soon as a task is presented, skills that are necessary to perform this task become active. The set of activated skills is a representation of the STM. The relation between skills can be described according to the architecture of memory: memory can be represented as a set of concepts that are connected by means of links that correspond to associations at the functional level (Dalenoort, 1985; Minsky, 1986). In analogy to a neural network, these links are represented by connections that can change in strength according to Hebb’s learning rule. All of the skills present in a single agent can be represented in a similar way: skills that are likely to be used together will have a stronger connection. We can illustrate this by using the example of the handyman and his toolbox (adapted from Minsky, 1986). For every job, before grasping his tools, the handyman paints his hands in a colour. For instance, blue is for repairing bikes, green is for making furniture, yellow is for repairing a roof. As a result of this the next time the handyman should repair a bike he simply picks the blue tools. Some tools may have more than one colour, because they are used for different tasks. The underlying principle: simultaneous activity causes a relation (same colour) which causes simultaneous activity, that can invoke Hebb’s learning rule.

2.4.2 Interaction at the skill level

On the basis of the cognitive architecture we discussed above, we shall now describe how agents interact. We stated that the actual use of a skill depends on motivation and expertise (see Figure 2). What would somebody do to perform a task if he lacks the skill or motivation to do it on his own? Ask for help! In the case of a single agent, e.g. John, we have represented the actual use of skills as active nodes (handling the helm and the sails) or passive nodes (watching the environment). In a multi-agent context, the agent may perform some skills individually, while other skills demand help. We may reformulate this as the choice: 'I will do it' or 'You will do it'. This choice will be made for every skill in every agent. In the case of John, who wants to sail by himself, these choices result in a: I, b: I, c: You (see Figure 2). This choice is solely based on the expertise and the motivation of a single agent, i.e. John. On the basis of this choice, he will influence another agent, but the final allocation has not been made yet. Therefore, we call this choice 'initial choice'.

John needs another crewman in his boat that knows how to interpret the motions of the other ships (e.g. to watch). Both Peter and Achmed know how to do this, but John knows that Peter likes to take the helm as well, which may result in a potential conflict whereas Achmed only likes watching other ships. Therefore John decides to ask Achmed to join him (see Figure 3):

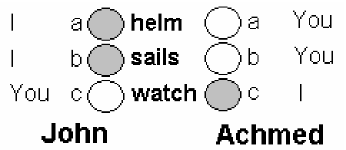

Figure 3: Complementarity of John and Achmed

John's decision is based on what is called 'complementarity of needs' (Kerckhoff & Davis, 1962): agents with initial choices that do not conflict are attracted to each other.

But how do these 'initial choices' affect each other? Again we will use the analogy to a neural-network model by using excitatory and inhibitory connections. The I-or-You-choice can be represented as two nodes of which one is activated. This node affects the I- and You-nodes of the other agents in the following way (see Figure 4a):

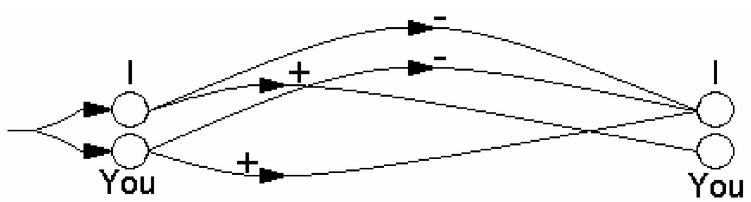

Figure 4a: influence between agents from one skill to another

If an I -node of an agent is activated, this node excitates the You-node of the other agent and inhibits the I-node of the other agent. An activated You-node excitates the I-node of the other agents and inhibits the You-node of the other agent. Hence, every skill that is activated within an agent may influence other agents by means of four possible connections (I-I, I-You, You-I and You-You).

The same obtains for the other agent: both agents will influence each other simultaneously (see Figure 4b):

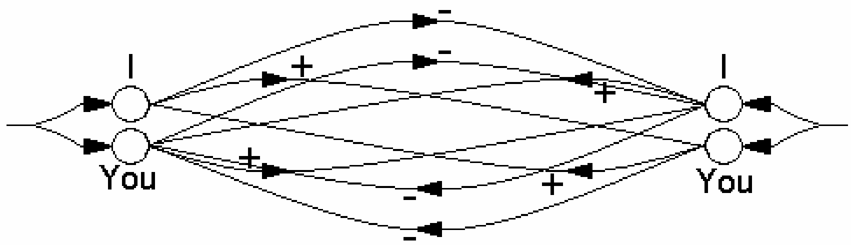

Figure 4b: Mutual influence between agents from one skill to another

This leads to the 'final allocation': if a skill must be actually used, it remains active until the task is finished. If a skill is not used after all, it becomes passive again.

2.4.3 The individual level: social interaction

In the previous section, we have described how expertise and motivation within a single agent lead to an 'initial choice', and how agents influence the choices of each other by making use of excitatory and inhibitory connections. After influencing and being influenced, the task is finally allocated to the agents. But how are these processes of allocation related to actual social behaviour? We have chosen to describe social behaviour by using two components, power and attraction. Consistent with our prior description of influence at the skill-level, we will use a neural network analogy to describe influence at the social level as well. But first, we shall give an overview of social psychological theories and models that describe processes of power and attraction in terms of social interaction.

Power can be described as the difference between the influence of A on B and the influence of B on A (e.g. Cartwright, 1959). Both Berger et al. (1974) and Latané (1981) stated that influence increases as status increases and status increases as expertise increases (Berger, Conner & Fisek, 1974; Latané, 1981). Within the context of task performance, processes of attraction are related to the preferences of co-workers. People will only be attracted to each other if they are aware of each other. Awareness increases as proximity increases (Festinger, Schachter, & Back, 1950). Since we discuss behaviour in a task-performing situation, attraction between agents can only increase if they work on the same task. This may be considered as a specific example of the similarity-attraction effect (Newcomb, 1960), which implies that attraction will increase as a function of the frequency of agents working together on the same task. The mere- exposure effect suggests that we like people whom we have been exposed to repeatedly (Zajonc, 1968). Each for its own specific condition, both the 'similarity attraction effect' and the 'mere-exposure effect' are analogous to Hebb's learning rule. Both approaches describe the emergence of a new connection and the strengthening of an existing one as a consequence of mutual activity (Zoethout, 1994; Nowak et al., 1998). Kitts et al. (1999) refer to this as ‘structural learning’.

In analogy to a neural network, connection strength between agents represents the amount of influence. Influence only takes place as a part of allocation processes. This implies that agents are only temporarily connected, i.e. if they are performing the same task. The property of ‘temporal connectivity’ is specific for social behaviour and does not apply to neural behaviour. An important component of social behaviour is distance (e.g. Festinger et al., 1950; Latané, 1981). This component does not play a significant role in neural networks because cognitive structures do not appear to be spatially localised in the brain (e.g. Dalenoort, 1982). However, for describing social behaviour, we use the concept of functional distance to describe the possibility of working together: as distance between agents increases, the possibility that they will work together on the same task decreases. Both agents are able to change the distance between them. If agent P becomes more motivated when he works together with agent Q, he will decrease the distance. However, if agent P becomes less motivated when he works together with agent Q, he will increase the distance. If P and Q are actually working together, they will influence each other. The power of P over Q is represented as the influence of P on Q minus the influence of Q over P (Cartwright, 1959). We stated that power increases as status increases and status increases as expertise increases. Only expertise that is actually used to perform a task will affect power, because expertise that has not been used is not socially present. At the skill level we stated that growth of expertise is represented as an increase of connection strength of the accompanying skill (see Figure 2). At the individual level, influence can be represented as the mean of all connection strengths.

2.5 Concluding Remarks

We have proposed a multi-agent architecture, which incorporates different psychological theories and models at different levels of aggregation. This makes the chapter susceptible to different disadvantages that arise from multi-disciplinary research. First we have the problem of different disciplines speaking different languages: the explanation of a multi-disciplinary model implies a carefully stepwise description to prevent misunderstanding (see also Klein & Kozlowski, 2000). Second we have the problem called ‘Bonini’s paradox’: ‘the more realistic and detailed one’s model, the more the model resembles the modelled organisation, including resemblance in the directions of incomprehensibility and indescribability’ (Starbuck, 1976, p 1101, cited in Weick, 1979). This refers to both multi-disciplinary research, and to the development of computer simulation models. In this chapter we have tried to overcome these disadvantages by describing both cognitive and social principles in terms of active and passive nodes and variable connections. This approach has forced us to look at the general principles behind a variety of existing theories and models. By using these principles we have simplified these theories and models and related them. In this way we think we have overcome the disadvantage of ‘ speaking different languages’ by making use of general principles the different theories and models have in common. The simplification of these theories and models should overcome the disadvantage of 'Bonini's paradox'.

A contribution to science refers to the need for integration of different theories and models into a meta-theory (e.g. Vallacher & Nowak, 1994; Jager, 2000). Moreover, both the studies of self-organising social systems and of social processes may make promising additions to existing social science. The contribution to society refers to the insights into group-dynamics of self-managing teams that may be used to enhance efficiency and effectiveness. Furthermore, the simulation model we described so far can be implemented within an organisational context, with organisational constraints such as fixed relations, limited space and time. Moreover, it is suited for conducting experiments regarding performance-criteria or learning. In short, the description of the hypothetical need for organisation in a task-performing context based on knowledge of human nature, will provide insight into social processes. This insight will be beneficial to both social sciences and management issues.