Self-organising processes of task allocation

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Chapter 6

Newcomers in Self-Organising Task Groups[10]

Abstract

This chapter describes the consequences of turnover, especially how a work group and a newcomer mutually adapt. We studied two types of groups that need an extra worker, either because of its workload, or because a former employee had left the group. For both groups, we tested conditions with newcomers being specialists, newcomers being generalists, and a control condition with no newcomer. We hypothesised that the group that needed an extra worker because of its workload would perform the best with a newcomer being a generalist. The group that needed an extra worker because a former employee had left the group, would perform better with a specialist newcomer. We studied the development of task allocation and performance, with expertise and motivation as process variables. The results only partly supported our hypotheses since both the specialists and the generalists only contributed to a better performance in the group that was left by the former employee.

6.1 Introduction

Suppose you are an employee working in a project team. Everybody is busy writing texts, printing, copying, putting covers on large piles of paper, and sell this to customers. Everyone knows what to do and everything works out fine like a well oiled machine, but an increasing workload causes everybody to work overtime in order to meet the deadline. Therefore, your team decides that you need an extra employee. And so happens. The new colleague is nice, works hard and tries to help wherever he or she can. But after a while it seems that you have made a mistake. Although the newcomer helps you fixing the team tasks, sometimes team members now have to do tasks they do not like or are less qualified for. In fact, since the entry of the newcomer the whole team seems to be imbalanced and performs worse.

This is an example of a newcomer influencing team performance negatively. The impact of a newcomer may partly be dependent on the type of the team task. Sometimes team performance is primarily determined by the best worker, such as in the case of specific mental tasks, or the worst worker, such as in an assembly line (e.g.

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[10] Submitted to Computational and Mathematical Organization Theory as Zoethout, K., Jager., W, & Molleman, E., Newcomers in Self-Organising Task Groups: When Does a Newcomer Really Contributes To a Better Performance?

Steiner 1972). But even when the interdependence among team members is rather low and workers perform an additive task (the subtasks are independent), where all team members contribute to the total, group performance may decrease when a newcomer joins the group. He may disturb the task allocation structure which may result in a situation that the old team members have to perform tasks they like and/or master less. Furthermore, when a newcomer is less experienced, he might perform tasks that some other team members could perform much better. Moreover, if more workers perform the same task this implies that there will be less chance for those workers to improve their skills concerning this task.

When does a newcomer in a workgroup contribute to a better performance? How is group performance related to the process of task allocation when a newcomer enters the group? Such questions pertain to the impact of turnover. Turnover refers to team members entering or leaving a workgroup or organisation, which often is associated with changes of performance and expertise (e.g.Levine, Moreland, Argote, & Carley 2005). These changes may have positive effects on performance, for instance when newcomers are highly skilled but also may be negative, if it disturbs a team's steady state (Levine et al. 2005). Moreover, the recruitment, selection, training and socialisation in general of newcomers may be costly to firms (Glebbeek & Bax 2004). On the other hand, prevention of turnover may also be expensive (Glebbeek & Bax 2004).

Literature mostly focuses on turnover being a dependent variable, whereas studies about the effects of turnover have been less emphasised (Glebbeek & Bax, 2004; Dineen & Noe 2003). Further, most of these studies only looked at outcome variables such as performance or transactive memory system (e.g.Levine et al. 2005), while neglecting the effects on group dynamical processes (Dineen & Noe, 2003). Others have studied process variables with membership change being an independent variable, but these studies either focus on conflict (O'Connor, Gruenfeld & McGrath 1993) or learning (Carley 1992), but do not involve task allocation processes (e.g. Marks, Mathieu, and Zaccaro 2001). Studies that have included team processes as an outcome of turnover mostly focus on general mechanisms regarding membership change (Dineen & Noe, 2003; Marks et al. 2001) or team processes in general (Arrow & McGrath, 1995) but focus less on the underlying processes such as social interactions. Moreover, although literature about person-job fit focuses on individual and organisational characteristics (e.g. Edwards 1991; Kristof 1996), it does not concern task allocation processes related to the mutual adaptation of newcomers and teams.

Thus, whereas the effects of separate variables – or limited combinations - have been empirically investigated, it is difficult to derive empirically based conclusions on how the combination of these variables affects the performance and its underlying processes of task allocation when a newcomer enters the team. Social simulation offers a methodology to systematically explore a large number of conditions, and thus may contribute to deriving such conclusions (e.g. Gilbert and Troitzsch 1999). In this chapter, by conducting experiments in which we vary characteristics of newcomers and tasks, we explore how newcomers affect the performance of a team and how a team and a newcomer mutually adapt. We study the effects of two types of newcomers, generalists and specialists, on two types of self-organising task groups. The first task group represents a project team in which the whole project was allocated to all members. This team needs an extra member because of its high workload. We hypothesise that this group will perform better with a generalist newcomer. The second task group represents a project team that recently lost one of its members. This team needs an extra member to fill in the gap that was created by the loss of his predecessor. We hypothesise that this group will perform better with a specialist newcomer.

In the first section of the chapter we focus on the theories and models we use and their formalisation, which form the basis of WORKMATE, the simulation program that we developed to study self-organising processes of task allocation (Zoethout, Jager, and Molleman 2006a; 2006b). WORKMATE is used to test hypotheses concerning the relation between different types of newcomers, task allocation processes, and performance. The second section describes the experimental design and the parameter settings. Next we will describe the results and we end up with conclusions and a discussion.

6.2 The Model

WORKMATE III is a deterministic discrete event based simulation program developed in DELPHI6 for simulating self-organising processes of task allocation. It is an elaborated version of the simulation program that we used for experiments on the emergence of job rotation (Zoethout et al. 2006a), and the relation between task variety and coordination time (Zoethout et al. 2006b). In this section we shortly describe the theoretical framework WORKMATE III is based on.

6.2.1 The multi agent system

An agent is a simple model of a human being with properties that are necessary to perform tasks. A task is considered as a set of actions in such a way that each action is related to a single skill (Hunt 1976; Weick 1979; Tschan & von Cranach 1996). During every timestep, i.e. round, each agent performs one action. The individual properties of the agents are represented as a set of skills. Each skill has two variable components: expertise and motivation, that are important components determining group performance (Wilke & Meertens 1994; see also Steiner, 1972). Skills are passive when they are not used and become active when they are needed for the performance of a task. When activated, a threshold function determines whether the agent actually wants to perform a particular action. This function implies that only if both expertise and motivation are higher than their thresholds, the agent wants to perform the particular action. In this way every agent chooses a subset of actions he would like to perform. If the choices of all agents imply that there are more agents sharing the same preference than there are actions to perform, the agents start negotiating. The negotiation process implies that the agents are trying to change the preferences of the other agents in such a way that the other agents will reach a complementary state with respect to their own (see also Zoethout et al. 2006b). The influence of the agents is based on their expertise and motivation of the particular skill, which implies that the agent with the highest expertise and/or motivation is more likely to get what he wants. The process ends as soon as the number of agents with a preference for a particular action is equal to the number of available actions. For instance, if we take a look at Figure 26, and we imagine that two out of three agents want to perform action a, in the first round, this will not be a problem. However, in the second round there is only one cycle of action a left, which means that they have to negotiate.

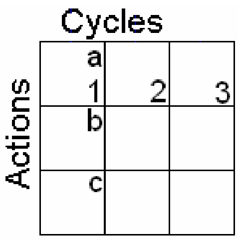

Figure 26: Actions and cycles

6.2.2 Task and task performance

Each action has to be performed a number of times, i.e. cycles, before it is finished. In this way, a task can be represented as a matrix of actions (what) and cycles (how often). In Figure 26 we see a task consisting of 3 actions, a, b, c and 3 cycles, i.e., 1, 2 and 3. Thus, the 3 actions need to be performed 3 times before the task is finished. The agents may perform the task in a number of ways, for instance cycle by cycle, action by action, or something in between. Two general allocation types, generalisation and specialisation bound the possible ways a task can be allocated. We use the concept of round to describe the specific order in which a task is performed. For instance, a group of specialists performs the task as depicted in Figure 26 in the following order; round 1: agent 1 performs action a1, agent 2 performs action b1, agent 3 performs action c1. At round 2, agent 1 performs action a2, etc. The number of agents that a group consists of determines the number of rounds it takes to finish the task. For instance, to finish the task as depicted in Figure 26, it takes 3 rounds for 3 agents, 5 rounds for 2 agents, and 9 rounds for 1 agent. Hence, it takes fewer rounds to perform a task when more agents are involved. This means that the concept of rounds indicates performance differences regarding experiments with groups with a variable number of agents. However, results that are based on this notion will be quite trivial. Instead we use a performance indicator that is corrected for the fact that more agents working on the same task imply fewer rounds to finish it. This performance indicator is based on a function of expertise and motivation being important components that determine group performance (see also Steiner 1972; Wilke & Meertens, 1994). Expertise and motivation may change as a result of task allocation and task performance. This implies that agents will increase the expertise of the skills they use and forget the skills they do not use. Furthermore, the motivation may change, i.e. the agents become bored after performing a particular action for a longer time and recover from it as soon as they stop (see also Zoethout et al, 2006a; 2006b).

Both expertise and motivation are defined in terms of the time it takes to perform a task: the higher the expertise or motivation, the sooner the task will be finished.

Furthermore, we define a minimal time to complete an action, t_{action}, which is equal to the actual time it takes to perform the action at a maximal rate of expertise and motivation. The actual performance time of a single agent, t_{per_agent} can therefore be expressed as:

$$t_{perf.} = \sum_{i=1}^{n} \frac{t_{action\_i}}{\lambda \frac{e_i}{e_{\max}} + (1-\lambda)\frac{m_i}{m_{\max}}} \tag{16a}$$

λ represents a parameter that determines the balance between expertise and motivation. n represents the number of actions that a task consists of. In our experiments we assume that expertise and motivation have the same effect on the performance time. This means that in the experiments λ is set on 0.5.

Since the actions of a task consists of multiple cycles, the total contribution of a single agent to the whole task can be expressed as:

$$t_{perf\_tot\_agent} = \sum_{j=1}^{k} \sum_{i=1}^{n} \frac{t_{cell\_ij}}{\lambda \frac{e_{ij}}{e_{\max}} + (1-\lambda)\frac{m_{ij}}{m_{\max}}} \tag{16b}$$

k represents the number of cycles that a task consists of. t_{cell_ij} represents the specific cell of the task matrix as represented in Figure 26. e_{ij} and m_{ij} represent the expertise and motivation at the moment the action of a particular cell is being performed.

In the present study, the agents perform the actions simultaneously. The task is being finished when all cycles of all actions have been completed. This means that the performance time of the group can be measured by taking the sum of the performance time of the individual agents:

$$T_{perf.} = \sum_{i=1}^{s} t_{perf\_tot\_agent\_i} \tag{16c}$$

s represents the number of agents that work on the particular task. Note that $T_{perf.}$ only indicates the total performance time based on the performance time of every agent per single cell, the number of cycles, and the number of actions. It does not concern the number of rounds that it takes to finish a task.

Thus, we propose a performance indicator that is corrected for the obvious benefit that more workers need fewer rounds to complete the task. Because of this, we are able to indicate the relative contribution of a newcomer. For instance, 2 groups of agents must perform the task as described in Figure 26. The first group consists of 3 agents, each having a total performance time of 100. This results in a group performance time of 300, whereas it takes 3 rounds to finish the task. The second group consists of 9 agents, each having a performance time of 40. This results in a group performance time of 360, whereas it takes only 1 round to finish the task. This implies that although it takes fewer rounds for the second group to finish the task, their performance is still worse because the first group performs its rounds a lot quicker than the second.

6.2.3 Model and hypotheses

We study performance and task allocation in relation to the task and the newcomer. Figure 27 gives an overview of the model in relation to the experiments that we conduct:

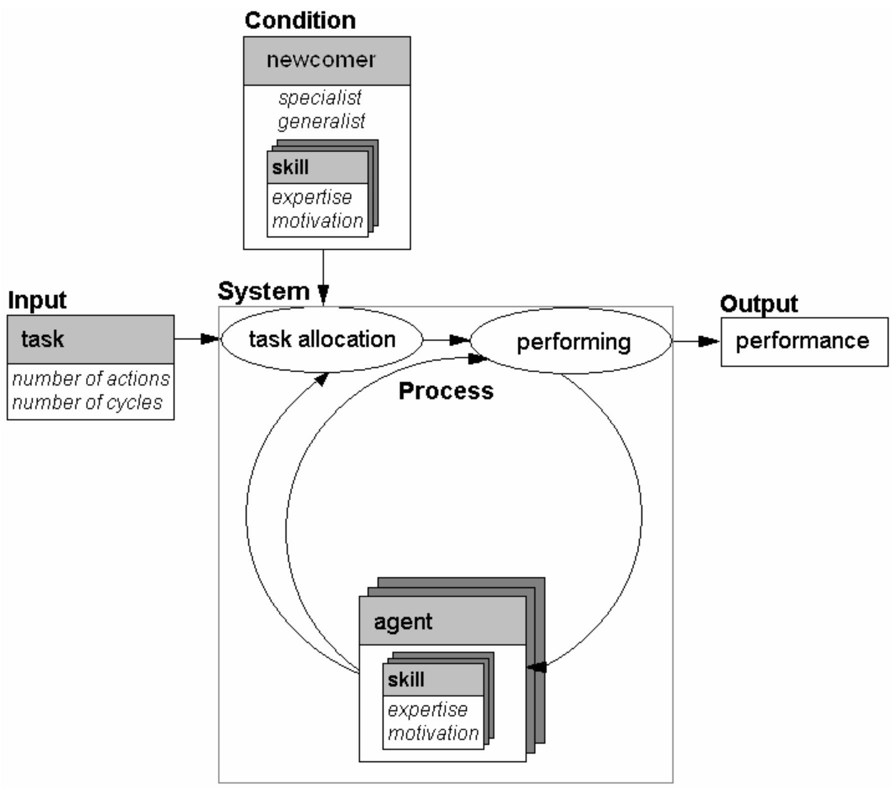

Figure 27: The model

The model can be described as a classic IPO (input-process-output) model as well as an IMOI (Input-Mediator-Output-Input) model (Ilgen, Hollenbeck, Johnson, and Jundt

2005). Being an IPO model, the Input is a task, consisting of a number of actions and a number of cycles. The Process is the combined process of task allocation, performing, and the changes in expertise and motivation of the agents within the system. The Output is the task that has been completed with a certain performance, which is the dependent variable. As an IMOI model, the Input is the task. Then, the task allocation (M) takes place on the basis of the expertise and motivation of the individual agents. Task allocation therefore depends on three sets of variables, the values of the task (number of actions and number of cycles), the values of the newcomer (expertise and motivation, specialist or generalist) and the values of the agents (expertise and motivation). On the basis of that, the agents start performing (O), which affects their expertise and motivation (I), etc. However, in our opinion, the discussion between IPO and IMOI is just a matter of choosing the system boundaries.

We studied two groups of 5 agents, a group performing a task consisting of 5 actions and a group performing a task consisting of 6 actions. The first group represents the project team that needs an extra co-worker because of its workload. 5 agents that perform a task of 5 actions will result in a symmetric task allocation in which the whole task is allocated evenly to all agents. The second group represents a project team that needs extra help because one of its members left the team. 5 agents performing a task of 6 actions will result in a asymmetric task allocation, with a 'gap' in which an additional worker may fit. We studied the effects of two types of newcomers, generalists and specialists. On the basis of these manipulations, we formulated the following hypotheses:

Hypothesis I: In a project team that needs an extra worker because of its workload, group performance will improve more when the newcomer is a generalist than if he is a specialist.

The rationale behind this hypothesis is based on the notion that a generalist is better able to perform all different 'loose ends' that the workers leave when they reach the end of the task. A specialist would only contribute when the group needs some specific skills. Therefore:

Hypothesis II: In a project team that needs an extra worker because one of its members left the team, group performance will improve more when the newcomer is a specialist on the part that the former member left than if he is a generalist.

6.3 Experimental Design

6.3.1 Variables and design

The experiment simulates a group of 5 agents who are all specialised in a particular part of the task. Although they do have the skills to perform the other actions as well, they have a clear preference to perform certain actions. Each agent has a different pattern of preferences. All agents are free to self-organise the task allocation whenever they want to, which opens the possibility of task rotation. Task rotation refers to the change of the preferences of the agents as a consequence of their expertise and motivational changes, which implies that they may wish to re-allocate their task.

We studied two groups, a group performing a task of 5 actions and 200 cycles and a group performing a task of 6 actions and 200 cycles. In the first group the agents easily develop a symmetric rotation mechanism. This mechanism holds that each agent rotates between his best and his second best skill. For instance, agent 1 rotates between action 5 and 4, agent 2 between 4 and 3, etc. With this rotation mechanism, it is hard for new members to easily fit in the existing task allocation process. Therefore, we labelled this condition as no fit. In the second group, because of the extra action, the agents allocate the task in an asymmetric way. Every agent still rotates between his best and his second best skill, but now 5 agents must allocate 6 actions, which leaves some kind of ‘gap’. This gap is likely to facilitate the adaptation of a new member. Therefore, this condition is labelled as fit.

Then the newcomer comes in. In both groups the newcomer starts at the 101st round. This offers the group enough time to have set the rotation mechanism and specialise further, i.e. to set a steady state that resembles a group of workers existing for a longer period of time.

We tested five conditions: Two conditions in which the newcomer is a specialist, with either low or high expertise and motivation, two conditions in which the newcomer is a generalist, with either low or high expertise and motivation, and one control condition with no newcomer at all. A specialist is defined as an agent with skills having all different values, which results in a preference for the best skills. A generalist is defined as an agent with all skills having the same value for motivation and expertise, whereas the agent must use them consecutively. Table 8 summarises the research design:

Table 8: Design

Newcomer\Task	5 actions (no fit)	6 actions (fit)
specialist low	C1	C2
specialist high	C3	C4
generalist low	C5	C6
generalist high	C7	C8
no newcomer	C9	C10

C1,…C10 refer to condition 1, …condition 10, also in the rest of the text. We choose two conditions for both the specialist and the generalist because these may indicate a range in which a newcomer actually leads to a better performance. We study the effects of these conditions on task allocation being a process variable, and performance being a dependent variable.

6.3.2 Agent values and parameter settings

The following parameter settings are equal for all experiments:

The system consists of 5 agents in the control condition + 1 newcomer in the other conditions

In the no fit condition, a task consists of 5 actions

In the fit condition, a task consists of 6 actions

The task consists of 200 cycles

The initial values of expertise and motivation are equal

The maxima of both motivation and expertise are set on 25

The motivation – and expertise thresholds are set on 9

The learning speed is 100

the forget speed is 3

The boredom rate is 100, the recovery rate is 100

The parameter values are not chosen on the basis of empirical criteria, since empirical studies that indicate such parameter values are yet to be done. Instead, we simply selected a parameter space that produced behaviour that we are interested in.

The newcomer comes in after 100 rounds. In the condition of no fit, the initial values of the agents are chosen as follows (see Table 9a):

Table 9a: First condition: 1 task of 5 actions (no fit)

Skill	Agent 1	Agent 2	Agent 3	Agent 4	Agent 5
1	*18*	*14*	*15*	*16*	*17*
2	*14*	*15*	*16*	*17*	*18*
3	*15*	*16*	*17*	*18*	*14*
4	*16*	*17*	*18*	*14*	*15*
5	*17*	*18*	*14*	*15*	*16*

The values (expertise and motivation) of the agents are symmetric. This implies that the performance of every agent will be about the same, whereas the agents are being specialised in different skills. Since the number of agents matches the number of actions the task consists of, they are more likely to develop a stable rotation mechanism. The initial values of the newcomers are chosen as follows: (see Table 9b):

Table 9b: Values of the newcomers in the first condition

Skill	Agent 6 (spec. low.)	Agent 6 (spec. high)	Agent 6 (gen. low.)	Agent 6 (gen. high)
1	*14*	*18*	*16*	*20*
2	*15*	*19*	*16*	*20*
3	*16*	*20*	*16*	*20*
4	*17*	*21*	*16*	*20*
5	*18*	*22*	*16*	*20*

Spec. low refers to the new agent being a specialist with low values, spec. high refers to the new agent being a specialist with high values, gen. low refers to the new agent being a generalist with low values, gen. high refers to the new agent being a generalist with high values. The specialist newcomer with low values has the same initial values as agent 2. All skill values of the generalist newcomer are the same.

The values of the agents in the condition of fit are described in Table 9c:

Table 9c: Second condition: 1 task of 6 actions (fit)

Skill	Agent 1	Agent 2	Agent 3	Agent 4	Agent 5
1	*18.5*	*13.5*	*14.5*	*15.5*	*16.5*
2	*13.5*	*14.5*	*15.5*	*16.5*	*17.5*
3	*14.5*	*15.5*	*16.5*	*17.5*	*18.5*
4	*15.5*	*16.5*	*17.5*	*18.5*	*13.5*
5	*16.5*	*17.5*	*18.5*	*13.5*	*14.5*
6	*17.5*	*18.5*	*13.5*	*14.5*	*15.5*

Comparing the tables 2a and 2c, we see that the initial values of the agents in the second condition differ from the first condition. The highest value of the second condition is 18.5 instead of 18 in the first condition. This is related to the number of actions the task consists of. Because of this, the values of the newcomers also differ (see Table 9d):

Table 9d: Values of the newcomers in the second condition

Skill	Agent 6 (spec. low.)	Agent 6 (spec. high)	Agent 6 (gen. low.)	Agent 6 (gen. high)
1	*17.5*	*21.5*	*16*	*20*
2	*18.5*	*22.5*	*16*	*20*
3	*13.5*	*17.5*	*16*	*20*
4	*14.5*	*18.5*	*16*	*20*
5	*15.5*	*19.5*	*16*	*20*
6	*16.5*	*20.5*	*16*	*20*

In both the no fit and the fit condition, the mean of the expertise and motivation of the agents in the group is 16. The mean of the newcomer with low values is 16. The newcomer with high values has a mean of 20.

6.4 Results

For every condition we analysed the performance time as well as the task allocation process of both groups. But first we will discuss how the different conditions are related to the total performance time after the task has been finished. In this way we hope to find an answer to the question, which group performs the best under which condition.

6.4.1 Total performance time

In the no fit condition, without a newcomer it took 200 rounds to complete the task. With a newcomer entering the group, at the 101st cycle, in all four conditions, it only took 184 rounds, i.e. 100 rounds without the newcomer and 84 rounds (which is about 5/6 * 100) with the newcomer. In the fit condition, without a newcomer it took 240 rounds to complete the task (which is 6/5 * 200). With a newcomer entering at the 101st cycle, in all four conditions, it only took 217 rounds, i.e. 100 rounds without the newcomer and 117 rounds (which is about 5/6 * 140) with the newcomer. Obviously, with a newcomer it takes fewer rounds to finish a task and it takes more rounds to perform the task of 6 actions in the fit condition, than the task of 5 actions in the no fit condition.

The total performance time for all conditions is depicted in Figure 28a and 28b.

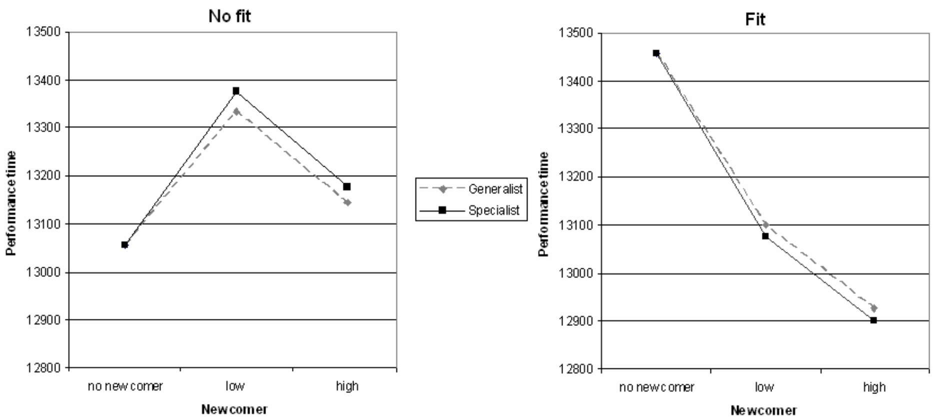

Figure 28a (left) and 28b (right): Total performance time of the groups in all conditions with specialists and generalists as newcomers

Low refers to a newcomer with low expertise and motivation and high refers to a newcomer with high expertise and motivation. The performance time in the figures is the sum of the performance time of all agents of all cycles, as indicated by formula (1c). In order to compare the data of the no fit (5 actions) and the fit condition (6 actions), we multiplied the total performance time of the fit condition with 5/6.

By comparing both figures, we observe four distinct effects. First, the performance time with no newcomer is better (i.e., lower) in the no fit condition (13055) than in the fit condition (13458,3). Second, in the no fit condition, all newcomers, both specialists and generalists, contribute negatively to the total performance time. Even a highly skilled newcomer only gets in the way, since the performance time without him is lower. In the fit condition on the other hand, all newcomers contribute positively to the total performance time. Third, the performance time of the group with the generalist newcomer is the best in the no fit condition. The group with the specialist newcomer performs the best in the fit condition. However, these differences are rather small. Fourth, and rather obviously, irrespective of being a specialist or a generalist, a newcomer with high expertise and motivation outperforms a newcomer with low expertise and motivation. Moreover, these effects are the same for both the no fit condition and the fit condition.

To better understand these findings, we must take a closer look at the underlying processes. In the next section we will therefore discuss some conditions in more detail, by giving an elaborate description of the development of the task allocation process and the performance time.

6.4.2 Underlying processes

In case there is no newcomer, the task allocation process in the no fit condition (C9) is quite simple: First, the agents start with their best skills. Then boredom forces them to rotate between their best and their second best skills until the task is finished. In the fit condition, the agents start in the same way. Based on the values in Table 9c. agent 1 performs action 1 and 6, agent 2 performs 6 and 5, agent 3 performs 5 and 4, agent 4 performs 4 and 3, and agent 5 performs 3 and 2. This implies that each action is performed by 2 agents, except for action 1 and action 2 that are only performed by 1 agent. These actions are performed after the agents have completed their best and second best action. Since the agents are less skilled in performing the remaining actions, performance time increases. Thus, the performance time with no newcomer is lower in the no fit condition than in the fit condition.

In the other conditions in which a newcomer enters the system after 100 rounds, the task allocation process can be described by using 3 phases. In the first phase, the agents start specialising a particular action until boredom forces them to rotate. In fact, this phase describes what happens with a group with no newcomer. In the second phase the newcomer comes in and starts performing. This implies that not all actions are finished at the same time. Phase 3 starts as soon as at least one action has been completely finished and the task must be re-allocated. After re-allocating the task, the agents proceed until another action has been finished, etc. In this serial way the agents continue until all actions have been completed.

In the last phase, there is a significant difference between the no fit condition and the fit condition that holds for all condition with a newcomer. In the no fit condition, the newcomer starts with his best two skills (or with his first two when he is a generalist) more or less in the same way as the other agents. Because the actions that the newcomer performs are also performed by some other agents as well (see Table 9a and 9b) these actions are finished first. From that point on, the newcomer switches to other actions to help the rest of the group. In the fit condition, the newcomer starts with his best two skills (or with his first two when he is a generalist). These skills correspond to the actions that were only performed by one agent instead of two. Being a newcomer, he starts later than the other agents. Therefore, his actions are finished later than the actions of the other agents. From that point on, the other agents have to switch to these actions to help the newcomer.

This means that in the no fit condition, in the third phase, the agents have to re-allocate a lot more than in the fit condition. This causes the main difference in performance time of both conditions. Although the ‘peaks’ in the third phase, representing the worst agent, are about the same in both conditions, we see a clear difference between the no fit and the fit condition during the third phase (see Figures 29a and 29b).

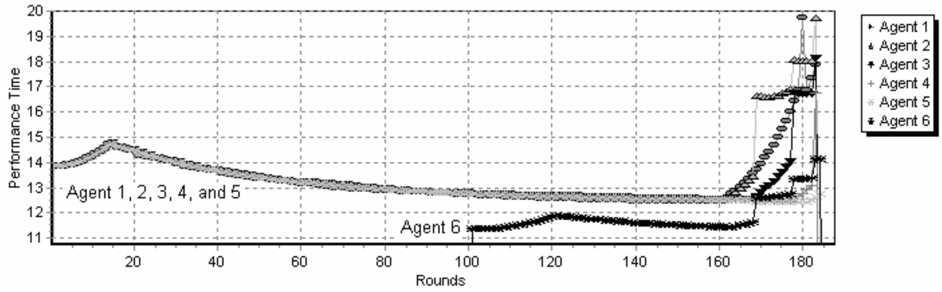

Figure 29a: Performance development in condition C3: no fit, high specialist

Figure 29a depicts the performance time (y-axis) at every round (x-axis), for all agents. During the first phase, all agents have the same performance time, which results in a single graph. From the 100th round, the newcomer enters the group, who initially performs better than the rest of the group. However, from the third phase (160th round), it turns out that the newcomer only appears to be in the way. His help during the second phase causes the other agents to shift to actions with low expertise and motivation. Further, the task allocation process is disturbed, which hinders the process of task rotation, which leads to further performance loss. This results in high peaks that are caused by agents working on actions they are least skilled for and by motivational decrease. Since the no fit condition with no newcomer shows no peaks at all, the group performs worse with a newcomer than without.

Figure 29b shows the performance development in the fit condition. Again the newcomer starts with a better performance than the rest of the group. From the start of the third phase (200th round), the performance peaks are about as high as in the former condition. However, because the agents do not switch that often, Figure 29b shows a graphic that is not as erratic as Figure 29a.

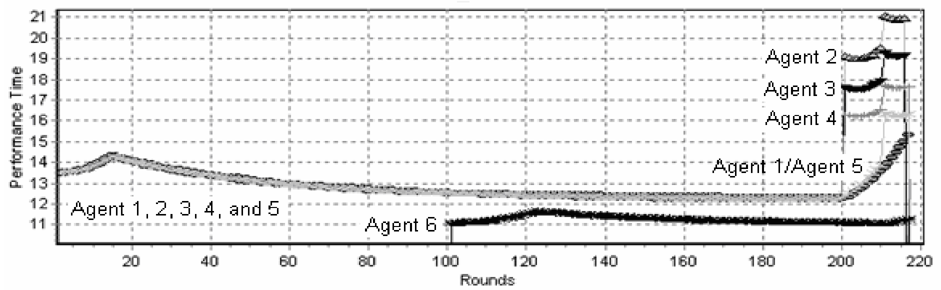

Figure 29b Performance development in condition C4: fit, high specialist

Thus, as regard the second finding, in the no fit condition, without a newcomer the task is performed quite well, with a nicely balanced task allocation process. When a newcomer enters the group, at first it looks that he is positively contributing. However, during the last phase, when everybody needs to help to finish the ‘loose ends’, it turns out that the newcomer is only in the way. Therefore, the no fit condition is better of without a newcomer. In the fit condition, when the newcomer enters, the specific task requires much more actions before it is completed than the other task. During the last phase all agents contribute evenly to this part. Because these agents are not highly skilled to do so, performance goes down. A newcomer, who is especially skilled in performing this specific part, contributes relatively more to team performance. Although at the end the ‘loose ends’ still cause high performance time peaks, performance with a newcomer is a lot better than without.

In the no fit condition, the contribution of a newcomer is dual. First, when he enters the group, his expertise and motivation lead to a better performance when his performance time is lower than the average group performance (i.e., he has high expertise and motivation). Second, during the last phase of task performance, he contributes to the ‘loose ends’ of the task. In the fit condition, during the last phase the newcomer simply continues with what he was doing (see also Figure 29b). Therefore, he does not contribute to the loose ends by re-allocating his actions.

Figure 29a depicts that in the no fit condition, the contribution to the newcomer to the last phase of the task is rather poor. In fact, because of this, the total performance time is lower than without a newcomer. Figure 29c depicts the performance time in the no fit condition when the newcomer is a generalist:

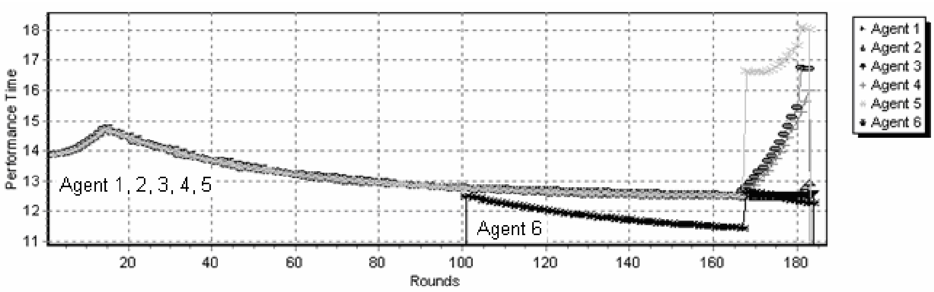

Figure 29c: Performance development in condition C7: no fit, high generalist

Instead of the initial increase, the performance time of the generalist newcomer immediately decreases: Because all his skills are identical he immediately starts rotating between two actions instead of building up boredom during the first 15 rounds. Because of this, his performance time in the second phase (100^{th} -167^{th} round), i.e. after he has entered the group, is somewhat higher than of the specialist in the no fit condition (see Figure 29a). However, the generalist newcomer is able to compensate for this by working on the different loose ends a lot better than the specialist newcomer. As regard the third finding, this explains why in the no fit condition, a group with a generalist newcomer performs better than a group with a specialist newcomer.

The benefit of the generalists in the last phase does not apply to the fit condition because the newcomer simply proceeds in what he is doing. Instead, the influence of the newcomer is only determined by his expertise and motivation in the second phase. Therefore, in the fit condition, a specialist newcomer performs better than a generalist newcomer. However, this benefit is quite small. The most important components that influence group performance time are the expertise and motivation of the newcomer. This explains the small differences in both conditions between the group with a specialist and the group with a generalist. Since expertise and motivation of the newcomer have a linear effect on group performance time, the slopes of the group with a specialist newcomer and the group with a generalist newcomer are the same. Further, the slopes of the groups in both the no fit condition and the fit condition are the same, which explains the fourth finding.

6.4.3 Acceptance of the hypotheses

Our hypotheses as formulated in 2.3 are based on the general idea that generalists may adapt more easily to a no fit condition because this demands a worker being able to work on multiple actions. A specialist on the other hand would be better able to fill the ‘gap’ in the fit condition. However, the results indicate that it does not matter that much whether the newcomer is a specialist or a generalist. Much more important is the possibility to fit in the group: In the no fit condition, none of the newcomers contributes positively to group performance, although the generalists contributed somewhat more than the specialists. On the other hand, in the fit condition, all newcomers improved group performance, whereas the specialists offered the best contribution.

On the basis of the results, the hypotheses are only partly supported. Hypothesis I, that stated that in the no fit condition group performance will improve more when the newcomer is a generalist than if he is a specialist, is not supported. Although group performance is better with a generalist than with a specialist, none of the newcomers actually improved group performance. Hypothesis II stated that in the fit condition group performance would improve more when the newcomer is a specialist than if he is generalist. Although the performance differences were small, this hypothesis is supported.

6.5 Conclusion and Discussion

We simulated the task allocation processes of two artificial work groups that both required an extra worker. The group in the no fit condition represented a project team in which the whole project was allocated to all members, whereas each member contributed evenly to the whole task. Because of the workload of the team it was decided, that an extra member would facilitate the work. We expected that the team would especially benefit from an extra worker when he was a generalist. However, the results showed that despite of the obvious benefit of more hands imply less work, the team did not benefit from a newcomer at all. This yielded for both specialists, and generalists, no matter how high their expertise and motivation were. The group in the fit condition represented a project team that recently lost one of its members. Although the remaining workers were able to finish the task, it was decided that the team was better of with an extra employee to fulfil the task. We expected that only a specialist would positively contribute to the team. However, it turned out, that any newcomer would come in handy, not only highly skilled specialists, but lowly skilled generalists as well.

On the basis of the results we may draw two conclusions. First, the general idea behind our hypotheses, that specialists will match the best with groups that have ‘gaps’ to be filled and generalists will contribute the best in groups without gaps, is only party supported. Although specialists actually fit in groups with gaps, generalists do not contribute in groups without gaps, since the benefit of more hands does not balance out the performance loss and costs related to hiring extra personnel. Therefore, we must conclude that only in groups with the possibility for a newcomer to fit in, a newcomer will contribute to a better performance. This implies that for a project team with a high workload and close to a deadline it only may seem a good solution to hire an extra worker. In practice, that worker may only hinder, decreasing group performance instead of contributing positively to the team.

Second, the results indicate that even in case of additive tasks the principle ‘the more workers, the better’ does not always apply. By using a performance indicator that has been corrected for the obvious benefit that more hands imply less work, we found that a newcomer only contributed to a better performance when a combination of the group and task structure offers a possibility to fit in. This not only yields for specialists but for generalists as well. When this possibility does not exist, disturbance in the allocation process will cause a decrease of performance caused by motivational decrease and ineffective use of capacities.

On the basis of this we may conclude that the combination of work group properties and task structure, as well as the task allocation process, are components that are more important than characteristics of newcomers. In general, the insights of our study may contribute to the existing literature of turnover, especially the studies that focus on team processes regarding newcomers (Dineen & Noe, 2003; see also Marks et al. 2001; Arrow & McGrath, 1995). In general, computer simulation is a useful method to understand group dynamical processes regarding newcomers. This yields not only for learning (e.g. Carley 1992), processes regarding the transactive memory system (Levine et al. 2005), or outcome variables such as performance (Levine et al. 2005), but for task allocation processes as well. Thus, to comprehend the mutual adaptation process of teams and newcomers, both computer simulation studies and the study of self-organising processes of task allocation may offer promising insights.

But to what extent is our study in fact useful? What do simulation results based on a simple model of a workgroup say about real life processes? First of all, we did not limit our experiments by using agents with cognitive properties only, but used a model in which we combined a simplified cognitive architecture with variable motivational states. Although this does not necessarily imply that the results of this study can easily be related to real life events, the combination of cognitive and motivational properties may result in more realistic dynamics than a model that only focuses on cognitive properties.

We used a performance indicator that we corrected for the benefit of more hands imply less work by constructing two ways of measuring the time that is necessary to finish a task. Both ways concerns the number of rounds, i.e. time steps, that workers need to finish a task: the first way is a function of task size and number of workers and the second way is based on the expertise and motivation of the workers. On the basis of this, we concluded that in some cases an extra worker did not benefit at all. However, we can imagine situations in which this conclusion does not hold. For instance, when a task can be split up in easy operational activities such as copying or printing, and complex activities such as writing text, a group would be able to finish a task a lot quicker with the help of some temporary workers, doing the easy work, while leaving the complex work to the rest of the staff. Moreover, the extra costs of recruiting and hiring extra personnel which lead to a less efficient way of task allocation are sometimes necessary, especially when the team has to meet a deadline. To enhance the realism of simulation studies about newcomers, these components may be studied in future research.

Future research may also involve task interdependencies and the motivation of the agents being dependent of the task, because one might state that every task contains elements that everyone likes or dislikes. We did not include this into this study because the then, the results were probably too complex to analyse. Only now that we comprehend the processes in a simpler way, we are able to add these components to study more realistic scenarios.