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Organizational Intelligence and Negotiation Based DAI Systems - Theoretical Foundations and Experimental Results

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Abstract

A steadily increasing number of researchers believes that so-called ’organizational’ multi agent systems are a key technology to support information and knowledge processing activities in cooperative, networked organizations. This, in turn, necessitates their integration with the underlying human-centred organization.

The concept of an ’organization’ has emerged as central to the structuring of activities of both decentralized industrial and commercial conglomerates and collections of intelligent problem solvers within Distributed Artificial Intelligence (DAI) systems. Of late a new discipline has begun to emerge, that of Organizational Intelligence (OI). Organizational Intelligence demands a greater synthesis between the principles of Organization Theory (OT) and DAI, by the explicit incorporation of theories of both organizations and DAI into the field of OI. This paper concentrates on two rather important features of OI, namely organizational memory and learning capabilities. It will first discuss the theoretical foundations. Then it will be shown how the contract net approach can be extended to meet these demands. Finally, it will be proved by some experimental results that the increased "intellectual" capabilities of the extended contract net will substantially contribute to the performance as well as the quality of solution processes.

1 Introduction

Today, organizations are faced with rapidly changing markets, global competition, decreasing cycles of technological innovations, world wide (and just in time) availability of information, and dramatic changes in their cultural, social, and political environments. In such highly dynamic environments, the expertise of many agents, both computational and human, needs to be combined and coordinated, in order to achieve effective and informed decision making. It is our belief that the organization of the twenty first century will not solely take account of the human factors, but will be comprised of human and computational agents and will be recognized as organizations within their own right. These computational technologies must be appropriate and amenable to assimilation into the organization.

Most strategies that have been developed to meet these challenges aim to enhance the organizational flexibility (short term) and adaptability (long term). Buzzwords such as downsizing of organizational structures, increased local autonomy, decentralisation, cooperation and team work, business process orientation and workflow management refer to organizational concepts that are considered in this context. However, it is commonly agreed that the ability of an enterprise to achieve competitive advantages in the market and to continuously survive in dynamic, often hostile environments largely depends upon its organizational information processing and problem solving capabilities. Consequently, organizational practitioners and researchers have focused their attention on the design of ’intellectual’ organizational capabilities such as organizational memory, learning, and communication. At the same time they reshape the scope of their analysis by claiming to explicitly integrate computer-based data and information processing technology into the body of organizational theory. Both trends unite in a new discipline that has begun to emerge recently, namely that of Organizational Intelligence (OI). OI can be defined as the intellectual capability of an organization, which integrates human and computational problem solving capabilities [KiOH95], [Mats88], [Mats92].

Recently, different computer-based approaches were analysed and compared with one another (cf. [Kirn94], [Romb93], [SyHa93] with respect to their ability to support information and knowledge processing activities between humans and computers in cooperative, networked organizations. While the evaluation of [SyHa93] is on a more general level, both [Kirn94] and [Romb93] especially investigate the capability of different computer-based approaches to meet the strong demands of organizational intelligence. All investigations came to the conclusion that DAI offers by far the most promising potential. However, although these results are rather encouraging they also showed that DAI techniques have some shortcomings. Among others, the integration with the underlying human-centred organization is an open question. However, organizational multi agent systems have to actively contribute to the "intellectual" capabilities of an organization and therefore have to support organizational features such as organizational cognition, organizational memory and learning, organizational problem solving, and organizational communication skills.

Within this context the paper starts with a brief introduction to organizational intelligence as defined by Matsuda (section 2). It will be shown that organizational process intelligence especially relies on an adequate support of intellectual organizational capabilities such as organizational cognition, communication, problem solving, memory, and learning. While the first three features are relatively well covered by DAI the latter two are only covered on a rather rudimentary level. In this paper we will concentrate on negotiation based multi agent systems, more precisely, on the contract net approach. Section 3 will briefly introduce this technique and present a solution for an extension of this approach by organizational memory and learning capabilities. In section 4 we will introduce a concrete scenario (the game "Scotland Yard") and show what organizational memory and learning capabilities mean within this scenario. In section 5 we will present the results of an experimental analysis and evaluation of the basic contract net approach and its extended version. It will be shown, that the increased "intellectual" capabilities of the extended contract net will substantially contribute to the performance as well as the quality of solution processes. Finally, section 6 will conclude this paper.

2 Theoretical foundations

As a theoretical concept T. Matsuda's OI-approach is of major importance in organization theory. He calls OI the "collective intellectual capability of an organization [...] in handling its problems" [Mats92]. This points to an integration of human and machine problem solving, so that this approach seems to be well suited for the above demands. In this section we will briefly introduce Matsuda's approach of OI and the capability of learning from the point of view of organization theory.

2.1 Matsuda's OI approach - a brief introduction

Following Matsuda's approach *organizational intelligence (OI)* can be interpreted as the entire "intellectual" manpower of an organization and therefore describes the collective problem solving capability of an organization. More specifically, OI consists of the totality of ordered information, experiences, knowledge and understanding. OI integrates the existing human and machine intelligence of an organization. *Machine intelligence* means the computer-based information and knowledge processing capability of an organization. OI can be viewed from two mutually dependent points of view: organizational intelligence as a (dynamic) process (*process intelligence*) and organizational intelligence as a (static) product (*product intelligence*).

Organizational product intelligence is the totality of all structured, synthesized and goal-directed information. It is generated when the information systems of an organization increases its problem solving capability. Three levels of product-intelligence can be distinguished: (1) *data* (physical in the nature and formal in its character), (2) *information* (purposeful sort concerning the goals of an organization) and (3) *intelligence* (that is to say actively used information). In order to achieve product intelligence, general rules have to be developed which permit the design of information systems in the OI sense.

Organizational process intelligence is the interactive, aggregative, and coordinative complex of human and machine intelligence within an organization. This implies that any (human and machine) intelligence is oriented towards workflows (processes). *Interaction* takes place not only between human and human but also between human and machine as well as machine and machine. Aggregation of intelligence takes place hierarchically: on the lowest level the knowledge of individual members of an organization is gathered. The next level is the level of groups, while the final one is the level of the organization as a whole. *Coordination* is of central importance, since it refers to both the execution of interactions and the aggregation processes.

Organizational process-intelligence can be subdivided into five parts.

1. Organizational memory

Organizational memory is the basic requirement for any kind of OI. It is the capability to store events, situations and both successful and unsuccessful behaviour and to remember this if required.

2. Organizational cognition

This covers the organizational perceptive and comprehensive capabilities, that enable an organization to concentrate on the essentials and have an influence on respectively can adapt future evolutions.

3. Organizational learning

This means the capability of an organization to use the knowledge which is stored in the organizational memory at the right time and to learn from the experiences made in the past. The learning refers to the behaviour in non-standard situations and the assessment of the (newly) developed way of acting.

4. Organizational communication

Communication describes the entire data, information and knowledge exchange between human and machine actors in the organization.

5. Organizational inference

Organizational inference not only covers problem solving. It also includes the avoidance, bypassing and encapsulation of a problem.

2.2 The capability to learn from the point of view of organization theory

As shown in other research work ([BoGa88], [MüWi93], [KiUn94]), multi agent systems (MAS) are well suited to solve complex and interdisciplinary problems in a flexible and autonomous way. From the features of OI discussed above they are especially strong in communication, cognition and inference. Not yet well examined are the questions, how multi agent systems do behave with respect to global memory and learning capability. This will be examined in this paper with respect to the contract net approach. We will start with a brief introduction into the foundations of organizational learning capability.

The *learning capability* of an organization depends on the individual capabilities of its members as well as on the forms of organizational connection between these members. The definition of the following learning concept originates from Foppa [Fopp68]. It will be taken as the basis for the further studies: "In the end the question in learning processes [...] is always, how an organism can adapt to the various requirements of its environment. However, the process of adaptability cannot be observed directly as it is possible with the 'memory'. We, therefore, do not observe the actual learning progress, but behaviour and its change. If someone repeatedly performs or omits something in a certain situation, that he omitted or performed in similar situations in the past, or if he reacts quicker or more safely, we will call this a learning process."

With this definition in mind, organizational learning can be observed on three levels.

1. The knowledge of an organization can be improved by individual learning of its members. However, individual learning does not automatically contribute to organizational learning. Duncan and Weiss [DuWe79] defined three demands, that must be met to make individual learning valuable for an organization:

- Organizational knowledge must be communicable; i.e., it must be expressed in terms that can be understood by the other members of the organization.
- It must meet with general approval as well. The members of the organization must accept it as useful knowledge.
- Finally, knowledge must be expressible in if-then relations. The connection of actions and its effects are mandatory for the creation of coordinated actions.

2. Learning within groups (group processes) constitutes the next level. Groups form the micro social unit for organizational learning. They integrate the existing experiences and capabilities of learning of its individual members. Whether a group behaves as efficiently as the best of its members or, to mention another extreme, even better than the sum of the capabilities of its members, depends both on the interconnections within the group and between the groups of the entire organization.

3. The macro structure constitutes the core of organizational learning. While the micro structure describes the interconnections within groups the macro structure concentrates on the interconnections between the groups of an organization. It is responsible for the success of the transformation process from individual and micro social learning to organizational learning.

The addressed levels will be analysed in more detail in the next sections.

2.2.1 Individual learning

Individual learning is the simplest form of organizational learning. It means that an organization profits from the acquisition of new knowledge by its members if this new knowledge is exploited in the sense of the organization. Individual learning can be subdivided in adaptive and innovative learning. *Adaptive learning* means to learn by imitating observed ways of acting. *Innovative learning* means to learn by models and simulations. However, it can only be applied if characteristics and features of the model can be presented by symbols. With the help of models frameworks for future behaviour can be designed and rehearsed, which results in an innovative way of acting.

There are quite a lot of (psychological) learning theories in the field of individual learning which we do not want to discuss here. The interested reader is referred, e.g., to Reber [Rebe89] for a summarized presentation.

2.2.2 Micro organizational learning

Micro organizational learning describes the next level and means learning on the level of groups. The capabilities and the knowledge of individuals can be exploited to treat and solve more complex problems which exceed the manpower of individuals. The efficiency respectively inefficiency of the teamwork essentially depends on group standards like confidence, openness, conformity and antagonism. By a proper choice of the concept of leadership positive influences can be strengthened.

However, in economic organization theory such social psychological features are second rate. Coordination between the group members and the organization as a whole is of more importance.

2.2.3 Macro organizational learning

Each organization possesses structural characteristics which were introduced to increase the learning capability of an organization. In this paper we will only refer to the well-established structures of organization theory, e.g. functional, self-constrained, project oriented and matrix structures ([DaSt86], [Khan77], [Gare91]).

The problematic nature of macro structures is caused by the opposite tasks of "distribution of labour" and "coordination of labour". On the one hand tasks must be standardized to achieve a simplification of the process sequences. On the other hand there must be a continuous development, from which standardized behaviour patterns can not be excluded. Therefore, there will always be tasks that differ from existing patterns and have to be treated individually. On the adaptive level, macro organizational learning is described by the capability of an organization to develop simple, standardized behaviour patterns on the level of macro structures. Innovative learning means, for example, the calculated unlearning of obsolete behaviour patterns. Knowledge and behaviour, prior assumed to be correct, can prove wrong or at least obsolete and, therefore, is no longer of any relevance.

By a change of the macro structure organizational (un)learning processes can be stimulated. Of course both necessary factors - time and resources - must be available because learning processes need both to be able to safely move from one solid state to another.

3 Extension of contract-net-based systems by OI-components

Cooperative problem solving is divided in the stages of problem decomposition and distribution, solving of the sub problems and the answer synthesis. If the allocation of the problem happens through negotiations between agents, this is called a negotiation-based multi agent system. The best known representative of those systems is the contract-net approach ([Smit80], [SmDa81], [DaSm83]). Here the problem is decomposed by a specific agent (the manager) in independent sub-tasks. These sub-tasks will be announced for solving to other agents. If an agent believes that he can solve an announced sub-problem, he sends a bid to the announcing agent. Based on the information in the bids, the manager selects the best suited agents and sends an award message to them.

Stephans and Merx [StMe89] summarize the performance results of four methods of solution with respect to six different scenarios of the pursuit problem[1]. One of the results of this research works was that negotiation-based systems are superior to autonomous agents. So far no studies have been made with respect to the question, in which way contract net systems are able to learn and to store the learnt things beyond the rudimentary individual level as a whole or at least in parts (learning on the micro- and macro organizational level). This question will be investigated in the following.

Even a brief analysis of the contract net approach shows that its strength are "flexibility / self organization" and "problem inference". Significant deficits can be found in the areas of "memory" and "learning" capability. An overall memory is neither at hand nor intended. The learning capability suffers enormously by this lack.

Therefore the next section presents a way of how to extend the contract net approach by an organizational memory.

Figure 1 shows a scenario with five agents. The dashed lines indicate the given possibilities for negotiation in the contract net. In the local databases the agents' individual knowledge is stored. To make this individual knowledge useful for the organization, that is to say to store knowledge on the group or organizational level, new structures are necessary. It is proposed to design an organizational memory for the entire MAS or for several groups of agents. The organizational memory can be implemented as an additional "memory-agent" (see fig. 1). This agent can either be addressed by new message types which have to be introduced or, in the

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1 The "pursuit problem" has been discussed by various researchers for several times, see e.g.: [BeJa88], [GaRo88], [Korf92], [StMe89], [StMe90], [Levy91] and our scenario

simplest case, the message types "request" and "information", as defined in the contract net protocol [Smit80], can be used. In a system like the one in fig. 1 organizational learning can be established on the individual level. Through the (semi-) autonomy of the several agents each one of them can have local knowledge, which he does not share with the rest of the system (organization). The knowledge that is made available for the organization is stored in the organizational memory. How the data is stored and how many agents share a common organizational memory is transparent to the individual agents.

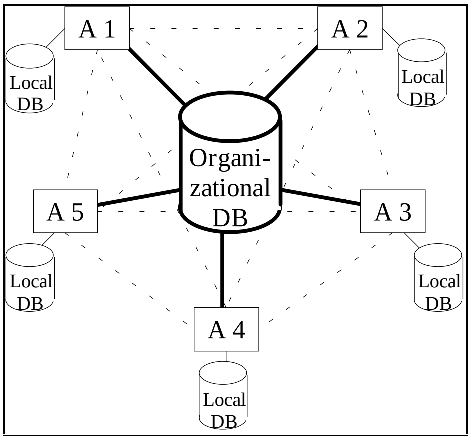


Figure 1: Extension of the contract net by an organizational memory

To realize the level of micro- and macro organizational learning within the contract net, a simple memory-agent will no longer be sufficient. As mentioned above, among other things the point for micro organizational learning is to choose the best suited concept in a given situation. This does not, or only on a rudimentary basis, exist in the contract net. There is indeed a message type called "directed award", which has been built in the protocol to avoid the negotiation process and therefore to be able to assign a task directly. To handle fuzzy, uncertain, non-monotonous knowledge etc. further extension must be made. Figure 2 shows the architecture we propose.

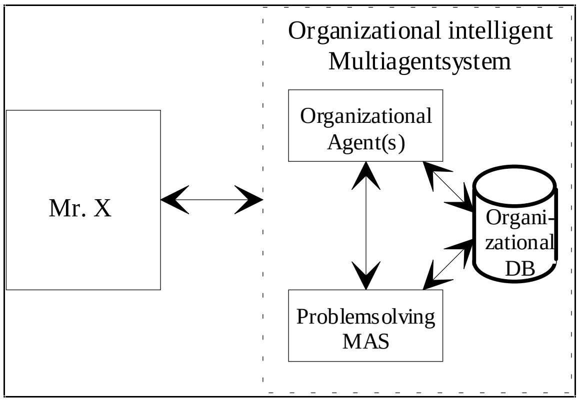


Figure 2: Extended multi agent architecture

The original MAS will be extended by a second level, the level of the so-called organizational agents. This organizational MAS is responsible for finding the coordination strategy best suited for the given situation and for the control of its realization within the problem solving MAS.

Both multi agent systems have access to the organizational memory (via the memory-agent(s)) so that organizational learning on the individual level can take place without incorporation of the organizational MAS. Negotiations take place on two different levels. On the problem solving level there is no change at all, whereas on the organizational level the strategy for the solution of the problem is regulated.

The advantages of the chosen architecture are:

- Neither the failure of the organizational memory nor that of the organizational MAS leads to a breakdown of the problem solving MAS because the negotiation mechanisms are still available.
- Because of the strict separation of the organizational extensions from the basic system, additional organizational and memory agents can be added later without any problem.
- Existing multi agent systems can be extended with less effort than if the organizational capabilities have to be implemented in each (problem solving) agent. In addition, the overall system has less redundancy.

At the moment there is no universally valid answer to the question of how many organizational agents will be needed and of how they must be conceived in respect to macro organizational learning, for example. This will one of the subjects our of future research work. In this context it seems to be interesting to include several organizational agents, which prefer different coordination strategies. These organizational agents would have to decide during a negotiation process, which strategy fits best in the concrete situation.

4 Realization in a scenario

4.1 Description of the scenario

In the following sections the extended contract net, as introduced in chapter 3, will be examined by a concrete scenario. The main question in this context is, how the efficiency and performance of such a system can be improved by adopting organizational memory and learning.

The implemented scenario is based on the game "Scotland Yard". A group of five agents tries to catch a runaway (called Mr. X) in a given number of moves. A simplified map of London with 199 fields is the playing board. The agents can move by taxi, bus or subway from one field to another, whereby the availability and radius of the different means of conveyance differ from one another (there are, for example, only 14 fields with a connection to the subway). Additional ferryboat connections can only be used by Mr. X. After each of his moves Mr. X has to announce, which means of conveyance he used. After several (individually regulated) moves during the game he has to tell on which field he is. The purpose of the game can only be achieved by a coordinated behaviour of the agents.

4.2 The basic structure of the system

Two scenarios have been implemented. One non-learning reference scenario and the proper OI-scenario, in which the concepts of chapter 3 have been implemented.

The implementation of Mr. X is the same in both scenarios. The multi agent system (MAS) of the non-learning scenario has been extended within the OI-scenario in such a way, that the concept of OI could be realized. The organizational MAS described in the previous chapter consists of exactly one agent who takes on the function of the organizational memory at the same time.

4.2.1 Implementation of Mr. X

Concerning the implementation of Mr. X it should be remarked that he behaves in a deterministic way. He will always make the same decision in the same situation. This is important for the learning of the MAS and will be assumed in the following sections.

4.2.2 Implementation of the agent system

4.2.2.1 The negotiation process in the problem solving system

The agents' negotiation process will be initiated, when one of them gets the information of Mr. X's last move. This agent therefore becomes the manager of the move and calls on his combatants to give him a list of their possible moves. The specific agent should sort this list in such a way, that his favoured move is at the top of the list. Based on these lists the manager computes the best position for all agents. The resulting moves are finally passed to the specific agents. In addition Mr. X. will be informed about the agents' new position.

The negotiation mechanism can be found in both the learning and the non-learning system. In the former it will only appear, if the situation is unknown to the system. In this case the move has to be negotiated, but then the manager is an organizational agent.

4.2.2.2 Learning within the scenario

Within the (OI-)scenario learning can be manifested on three levels. On the simplest level there is the learning of the single agents (*individual learning*), that is, an agent can act faster, though he only has the same information. This means for example that an agent does not need any longer to compute a proposal, but can refer to a prior stored one. The time of his reaction (defined as the difference between the moments of the request and the answer) will on average decrease significantly (point (2) of the learning concept).

Learning on the level of the system is reflected by changing coordination mechanisms (*micro organizational learning*). In this scenario the result of a learning process is, that, if the global state of the system is known, the allocation of the moves to be executed can be made directly, that is without the collection of the proposals.

In this scenario *macro organizational learning* means the calculated unlearning of former re-actions to a specific state of the system. The space to be searched, that is to say the fields, on which Mr. X. could be, can for example be reduced by examining two successive states. The resulting new information can cause the system to deviate from the reaction that was assumed to be "optimal" up to that time.

Example:

The data in this example are based on a real part of the playing board.

position of the agents	*possible position of Mr. X*	*Flag*
63,78,82,109,131	64,80,81,98,112,114,125	NF
64,79,81,110,125	not interesting in this context	NF

Table 1a: hypothetical part of the organizational memory

The abbreviation "NF" in the column "Flag" indicates, that Mr. X was **n**ot **f**ound in the states i and i+1. By the choice of moves, that led to state i+1, Mr. X was not found.

This is why the following can be deduced with the help of proper algorithms.

no. of move	*position of the agents*	*possible position of Mr. X*	*Flag*
i	63,78,82,109,131	64,80,81,98,112,114,125 (limited to 80, 98, 112, 114)	NF
i+1	80,79,101,110,114	not interesting in this context	NF

Table 1b: hypothetical part of the organizational memory

The change in the agents' behaviour can be explained by the failure of the initial version. If the same state of the game is reached again and Mr. X is not found with the agents' new position the space to search can be deduced to two fields (98 and 112).

The following section shows, how the negotiation mechanism works when organizational memory and learning are included in the scenario.

4.3 Schematical run of a move in the OI-scenario

Figure 3 shows the run of a move in our scenario.The agent who receives the information of Mr. X´s move creates a *OI-task* message which activates the organizational agent. Thereby he becomes the manager of the move. For the choice of the coordination strategy he refers to the organizational memory. If he finds data that are suitable for the current situation the negotiation process can be dropped and the tasks will be directly allocated to the agents. Otherwise the organizational agent initiates the negotiation process.

The boxes with the thick border represent the involved agents resp. Mr. X. Boxes with a thin border indicate the actions to be executed by the organizational agent.

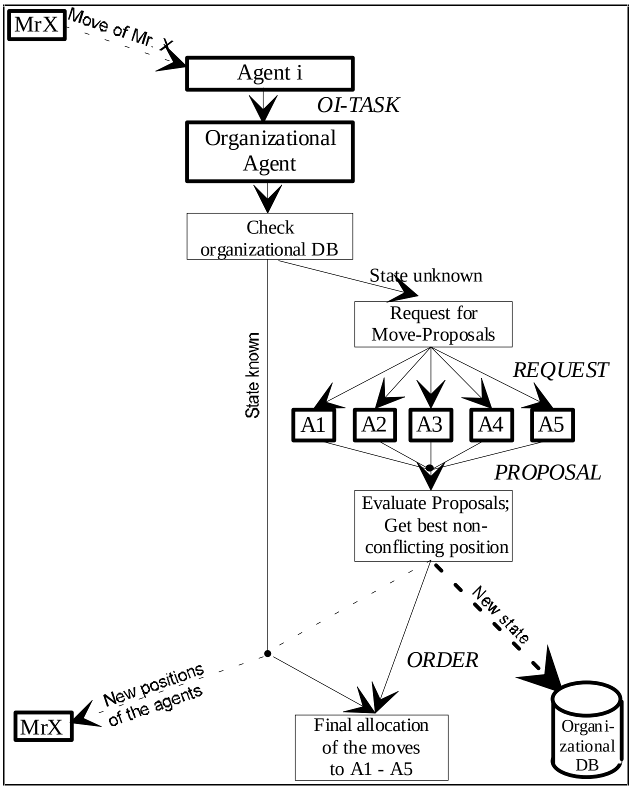


Figure 3: Run of a move

5 Presentation and Evaluation of the Results

Based on the scenario mentioned above, this chapter will illustrate in how far an extended contract net (eCN) that is extended by organizational memory and learning ability offers a faster and/or improved solution as opposed to the conventional contract net (CN) without learning capability.

Preliminary remarks:

The following considerations on complexity clearly show that the series of tests can cover only a small range of possibilities.

- *Starting positions:*

  According to the rules of the game, there are 20 potential starting fields for the agents and Mr. X. When the possible starting conditions are calculated,

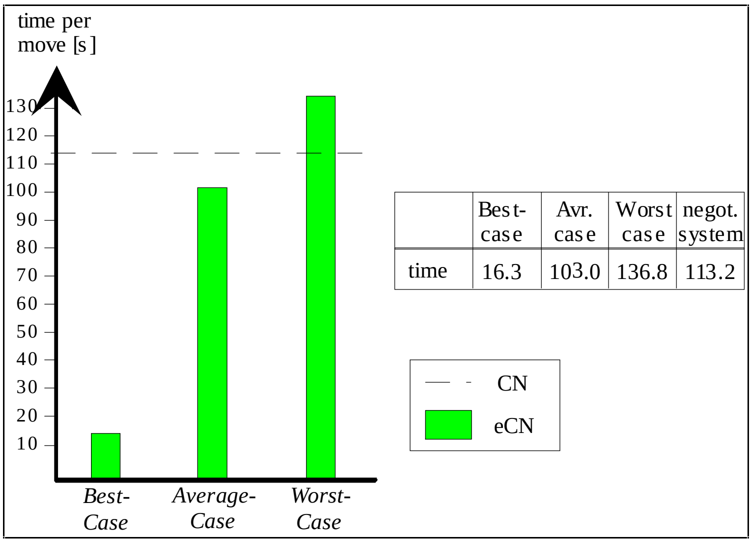
  $\binom{20}{6} = 38760$ different positions are obtained.

- *Size of state space:*

  When trying to store in the organizational memory all states of the game, when Mr. X is visible on the board, approximately $8*10^{10}$ records are obtained. Adding those situations when Mr. X is invisible and could stay on exactly two fields, the order of magnitude of $4{,}6*10^{13}$ records is already achieved. These numbers clarify already that it is impossible to store the total of possible states of even this small scenario in the organizational memory. It is only possible to manage a small part efficiently.

Due to the large amount of possible starting situations, a clever selection of similar positions had to be made to guarantee that the agents could meet with already known system states during the game. This method can be justified considering the fact that generally the space to search in real organizations is definitely smaller. Several series of tests were gone through, thereby slightly changing the game parameters (e.g. different number of moves after which Mr. X must reveal himself). Since all series of tests principally led to the same results, only one series of tests will be presented in detail and analysed in the following. Starting with a system with an empty organizational memory, from a basic set of 50 different starting positions 30 were arbitrarily chosen and played one after another. The games were not played through, but finished after a fixed number of moves. In the system with memory, new game constellations were stored so that the system became "more intelligent" with increasing numbers of games. It should be mentioned that due to the enormously high number of possible game constellations the organizational memory in our series of tests has always shown a linear increase.

Comparison conventional ↔ extended contract net



	Best-case	Avr. case	Worst case	negot. system
time	16.3	103.0	136.8	113.2

Figure 4: Comparison CN ↔ eCN

Figure 4 shows a comparison of the performance of the eCN with the CN. For this, the moves in the eCN were classified in two categories and the average determined for each category. In the Best-Case, the move is already contained in the organizational memory and must therefore not be negotiated. The Worst-Case means that the move must be negotiated. The Average-Case indicates the average time that was needed to decide a move in the eCN. The dashed line marks how long the negotiation of a move would have taken in average for the CN. The graphic shows that the gain in time for a move that must not be negotiated is considerable. For the measured data, the factor lies at almost 7 (for other series, it even nearly approached factor 10). However, despite of favourably chosen starting positions, not even every 12th move was already stored in the organizational memory. For this reason, the average time per move is only about 10% lower than the time needed for negotiated moves. Through the extreme examples "Best-Case" and "Worst-Case" and the very small organizational memory in the test it is to be expected that the efficiency gains of the eCN can be still increased in further test runs. This holds particularly true, since - owing to the fixed number of moves - our test scenario does not consider the fact that the eCN has the ability to learn and will therefore select increasingly more favourable moves in the course of the time, thus increasing the probability that Mr. X is caught considerably more quickly.

Furthermore, figure 4 informs about the possible potential of efficiency gains of the eCN compared to the CN. If all moves were already stored in the organizational memory, the "best-case" would become the normal case. According to the graphical representation, an efficiency increase by factor 7 would thus become possible. The following analysis, however, shows that this statement should be made with care.

Size of Organizational Memory

Figure 5 reflects an analysis on the relation time per move and the size of the organizational memory. This relation is first characterized by clear efficiency gains (shortening of time per move) and a simultaneous increase of the organizational memory (medium-grey area). These gains quickly decrease in the light-grey area and become zero at the intersection of the light-grey and dark-grey area of the relation. The dark-grey area is finally characterized by an increasing organizational memory and a simultaneous decrease in efficiency.

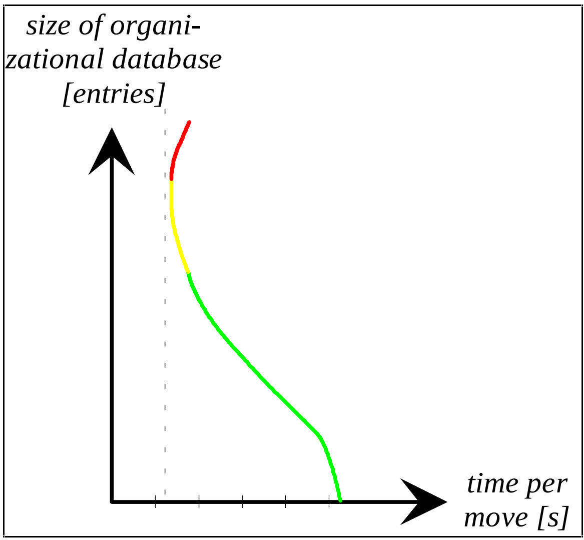


Figure 5: Time per move in dependence of the size of the organizational memory

The decrease in efficiency and its final reversion into the negative are caused by the overhead for searching the organizational memory. From a certain size the time needed for searching a position is greater than the time saved. By means of the potential order of magnitude of the organizational memory, which was calculated in the preliminary remarks of this chapter, it can be understood that these are no irrelevant assumptions.

Time Needed for Negotiated Moves

Figure 6 shows the range of deviation for the time needed for negotiated moves in the eCN scenario. For representing the deviation range, 10 equidistant intervals with length 15 and one open interval (length of move > 150 s) were selected and the number of moves, which fall in these intervals, were marked.

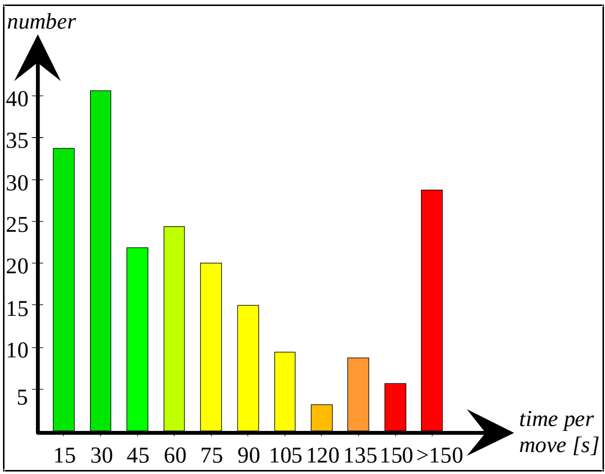


Figure 6: Range of deviation for the time needed for negotiated moves in the eCN

It can be deduced from the graphic that there are considerable time differences between moves already stored in the organizational memory and moves which have to be negotiated first. The following causes can be responsible:

1. **Unsuccessful search in the organizational memory**

   Since only after comparison with all data of the organizational memory it has been settled that the searched state is not stored (negative decision), it can be assumed that unsuccessful searching in the organizational memory takes twice as long on average as in the case of a positive decision, provided that the search is linear (as is the case in our scenario).

2. **The negotiating mechanism**

   The time needed for negotiation may be subdivided into time consumed for communication and into time that each agent needs for calculating his proposal. The communication time of the agents for exchanging the order and the resulting data may be neglected due to the software architecture. The time which each agent needs for drawing up his proposal list is of greater interest. This time, in turn, is dependent on the agent's actual position (how many possible successive fields exist?), the number of possible fields of Mr. X and on the distance between his successive fields and the positions of Mr. X. The required time increases in proportion to the number of possible successive positions of Mr. X.

3. **Elimination of conflicts**

   Elimination of conflicts is a factor that is of no small importance. A conflict occurs if at least two agents indicate the same field to that they both want to move. By eliminating this conflict, new conflicts can arise so that great efforts to eliminate them may be required. The following example illustrates this situation:

<u>Example:</u>

Two starting positions are given.

no.	*starting position of the agents*	*position of Mr. X*
1	10, 50, 76, 79, 182	196
2	5, 6, 7, 16, 30	196

For those positions results:

no.	*number of moves to be checked*	*time needed*
1	20	54
2	11	78

Although for the first starting position almost twice as many successive fields have to be checked, the time needed amounts to only 2/3 of that of starting position 2. This is due to the fact that starting position 1 is free of conflicts, whereas for starting position 2 many conflicts have to be solved first.

The above considerations suggest a classification of the negotiated moves into three categories. The first category (medium-grey) is characterized by a conflict-free position and only few possible fields for Mr. X. In the second category (light-grey), either conflicts occur or the number of possible fields for Mr. X is relatively high. The last category (dark-grey) combines both negative properties.

On the whole, the graphic depicts that a really "intelligent" system should not store all game constellations, but only those which do at least not belong to the medium-grey category. Thus it is guaranteed that on the one hand, the memory does not increase too much, and on the other hand, in case of a hit a profit as high as possible is obtained.

6 Conclusion

This paper has outlined that a contract net can be extended by an organizational memory and learning capabilities in a way that it meets the high requirements on computer-aided systems to a high degree. The simulations performed with the help of a game scenario have shown that an extension of the contract net by an organizational memory can considerably improve efficiency and capacity of this approach.

In further research, on the one hand our simulations will be further improved by including other DAI-approaches into our series of tests, thus allowing a comparison of different DAI-approaches. Simultaneously, we will continue to work on construction and performance of the organization MAS of our extended contract net. In particular the question is concerned how many and which organization agents can be linked in which way.

The long-term goal of the research work is to design a concept that organizationally intelligent MAS can be productively used within real organizations. Whether this goal can be achieved, depends very much on the success of designing a reference architecture for cooperative (DAI) systems. Such an architecture is necessary in order to enable the integration of different software systems.

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