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Behavioral Analysis of Team Members in Virtual Organization based on Trust Dimension and Learning

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***Abstract*—**Trust management and Reputation models are becoming integral part of Internet based applications such as CSCW, E-commerce and Grid Computing. Also the trust dimension is a significant social structure and key to social relations within a collaborative community. Collaborative Decision Making (CDM) is a difficult task in the context of distributed environment (information across different geographical locations) and multidisciplinary decisions are involved such as Virtual Organization (VO). To aid team decision making in VO, Decision Support System and social network analysis approaches are integrated. In such situations social learning helps an organization in terms of relationship, team formation, partner selection etc. In this paper we focus on trust learning. Trust learning is an important activity in terms of information exchange, negotiation, collaboration and trust assessment for cooperation among virtual team members. In this paper we have proposed a reinforcement learning which enhances the trust decision making capability of interacting agents during collaboration in problem solving activity. Trust computational model with learning that we present is adapted for best alternate selection of new project in the organization. We verify our model in a multi-agent simulation where the agents in the community learn to identify trustworthy members, inconsistent behavior and conflicting behavior of agents.

***Keywords*—**Collaborative Decision making, Trust, Multi Agent System (MAS), Bayesian Network, Reinforcement Learning.

I. Introduction

MODERN organizations have adopted decentralized, team based, distributed structures of virtual organization. A virtual organization (VO) is defined as a geographically distributed organization whose members are bound by a long-term common interest or goal and who communicate and coordinate their work through information technology [20]. The activities of virtual organization will depend highly on a new form of organizational unit known as the distributed group. These groups must rely on technological support to bridge the geographical gap between its members in order to effectively communicate and coordinate organizational activities. The distributed group needs to effectively combine the available information and expertise into effective decision making against the constraints imposed by geographical separation. Many virtual organizations take advantage of current development in Computer Supported Cooperative Work (CSCW) to effectively coordinate resources (e.g., information, expertise, production capacity etc.) [16]. CSCW or groupware concentrates on applying communication and information technologies to the problem of supporting and enhancing group interaction and decision making activities.

Existing groupware have emphasized technological issues such as group memory, communication tools [5] [6]. Social issues such as roles, relationship, trust, reputation are common to any organization [17]. But CSCW designers need tools to integrate these social issues in groupware. In order to effectively support group participation (Virtual Teams) in organizational decision making, social collaboration models and decision analysis tools must be integrated. These integrated tools support to analyze the system and the work of groups which use them. Aspects of cooperation and collaboration, and role of trust in group decision making plays an important role in Virtual Organization [24]. Sociologists and psychologists have been studying social networks in human societies for a long time and these social networks can be used to analyze trust and reputation [25]. These studies show that it is possible to say lot about the behavior of individuals using the information obtained from the analysis of their social network. Hence behavior of team members in distributed group or Virtual Organization and virtual teams are analyzed based on trust factor and Distributed Artificial Intelligence (DAI) [14] techniques and Multi- Agent Systems [15] in this paper.

Trust is a basic feature of social situations and plays a critical role in problem solving, organizational performance and organizational communication [11]. We are more concerned with cooperation and collaboration in group decision making in VO. In our previous paper [2] we have presented an agent framework for collaborative decision making and a Trust computational model [1]. In this paper we mainly focus on learning trust improve cooperation and coordination among team members.

Trust learning is a very important aspect in Virtual Organization. Learning in multi-agent systems (MAS) [22] are a field of study of growing interest in a wide variety of domains, and especially in Virtual Organization. Learning

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from reputation and recommendation in social networks are integral part of application involving Internet communication such as Grid Computing, Virtual Organization. Learning among virtual team member during collaborative interaction greatly helps in organization functionality and progress.

One of the most active research areas in artificial intelligence devoted to learning through interaction with the environment is reinforcement learning [26]. We have used reinforcement learning, where agents learn to make trust decisions, which improve agents trust behavior. While agents learn about recommenders and other interacting agents in a team, it improves group outcome in terms of cooperation and trusting behavior. This formalized trust model based on Multi-Agent System (MAS) aids recording of social events during collaboration, which helps in revealing the evolution of relationships, behavior of members in a given context and facilitates the capture of rich data about the group process.

The next section will discuss related work. Collaborative decision making framework and Trust computational model is presented in section III. Section IV describes reinforcement learning. Experimental work is presented in section V and section VI draws conclusion.

II. Related Research

Trust is one of the most valuable group components and is essential to the process of group influence and collaboration [18]. Several researchers [10] [11] [12] have tried to compute trust in various environments. Much of the research work on the concept of trust is for E-commerce and On-line recommendation systems [13], pervasive computing etc. Trust modeling for Virtual organization for coalition [19], partner selection for improving business [20], cooperation mechanism for team work [21] is some work in the field of MAS and CSCW. MCDM and decision support systems are integrated in many research work [8] [9].

Learning is a crucial aspect of information exchange [23], negotiation, group decision making and any other kind of social interaction among autonomous agents in Computer Supported Cooperative Work (CSCW) in VO. Reinforcement learning (RL) concerns the problem of a learning agent interacting with its environment to achieve a goal. Reinforcement Learning methods are often applied to problems involving MAS cooperation. Multi-Agent Reinforcement Learning (MARL) algorithms is presented in [26]. In this work, a supervision framework to speed up the convergence of MARL algorithms in a network of agents is discussed. The framework defines an organizational structure for automated supervision and a communication protocol for exchanging information between lower-level agents and higher-level supervising agents. Incremental reinforcement learning for large Markov decision process with MAS is implemented in [27]. Decentralized reinforcement learning in cooperative MAS is presented in [28], where a team of independent learning robots try to coordinate their individual behavior to reach a coherent joint behavior.

Q-learning, iterative learning approach is dealt in [29]. But most current probabilistic models for computational trust learning lack the ability to take context/domain into account when trying to predict future behavior of interacting agents. In this paper we focus on learning trust factor based on reinforcement learning considering domain, similarity in domain and past experience to compute direct trust.

III. Collaborative Decision Framework and Trust Model

We have proposed a Collaborative Decision making agent framework [2], Consensus algorithm [3] [4] and Trust computation model using Bayesian network [1] in our earlier work. In this paper we have focused on learning block of the framework in Fig. 1. We have proposed reinforcement learning to improve the trust belief of an agent.

The overall trust of an agent is computed based on direct interactions of an agent represented by Bayesian network [1] and recommendation from other agents (posterior probabilistic value) as shown in Fig. 2. This overall trust is used by an agent to decide whether to cooperate with other agent or not for task related activity.

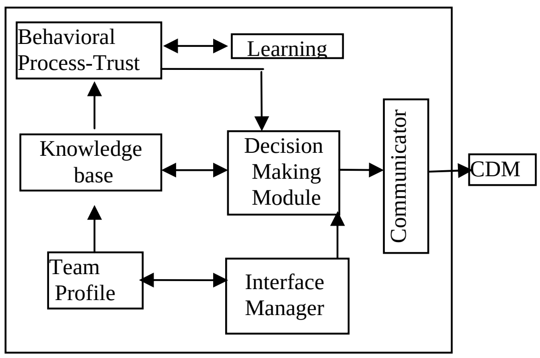

Fig. 1 Collaborative Decision Making agent

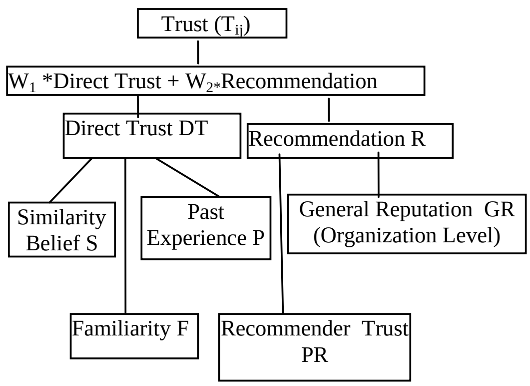

Fig. 2 Structure of Trust Computation

A. Recommendation and Reputation

Although direct interactions are the most reliable source of information, whenever agent has less interaction, it is not possible to rely only on direct interactions. It is in these situations the social dimension of an agent may help by using information coming from others. The General Reputation GR acts as witness reputation from others in organization. The GR is determined at organizational level and available in team profile of an agent in framework as shown in Table I. GR is computed based on questionnaire based reputation acquisition process. In this process each agent in an organization is given a simple questionnaire in which each agent has to estimate its past collaboration (any domain/ context) with other agents. The aggregated numerical value is represented in team profile as GR in the range [0 1].

TABLE I
GENERAL REPUTATION AT ORGANIZATION LEVEL AND ITS RANGE

GR	***Value***
High	0.61 to 1
Low	0 to 0.6

Once an agent computes Direct trust DT [1] about other agents in the group, then an agent Ai collect recommendation R from other agents about A_j. Other agents in team use General Reputation GR from team profile to compute Recommendation R about agent A_j and their Direct Trust DT and send it to agent A_i. Agent A_i collects recommendation from all other team members and stores it as R_{ij}. Using Bayes' rule, given recommendation from k distinct agents in team, the posterior probability is computed as P[GR/R] as in equation 1.

$$P[GR/R] = \frac{P[GR]\prod_k P[R_k^i/GR]}{P[GR]\prod_k P[R_k^i/GR] + P[\overline{GR}]\prod_k P[R_k^i/\overline{GR}]} \quad (1)$$

where i $\in$ {0 1} and $P[R_k^i/GR]$ is the probability that agent k confirm General Reputation GR, given GR is true. The Recommendation trust(PR is obtained from Direct trust) value computed by an agent is mapped to 0 or 1, to represents recommendation weight. $P[R_k^0/GR]$ is the probability that agent k does not confirm GR, given GR is true and $P[R_k^0/GR]$=1- $P[R_k^1/GR]$. This is equivalent to an agent A_k do not recommend agent A_j even though the GR is true. After computing the posterior probability for recommendation, each agent A_i stores R_{ij} as P[GR/R], recommendation value for agent A_j. R_{ij} represents the aggregated recommendation from different agents about A_j, and received by agent A_i. This value is used in computation of overall trust.

B. Overall Trust and Cooperation

The direct trust and recommendation of other agents are combined to compute overall trust T_{ij} of agent A_i about agent A_j as in equation 2 and w_1 and w_2 are the importance assigned by agent Ai to weigh the direct trust and recommendations as in equation 2.

$$T_{ij} = \alpha\ (w_1 DT_{ij} + w_2 R_{ij}) \quad (2)$$

where α is the normalization factor. If this value of T_{ij} is above Cooperative threshold θ_2 ($T_{ij} > \theta_2$), then agent A_i cooperates with agent A_j so that decision of agent A_i and A_j are same about the alternate selection. Agent A_i trust A_j in deciding one alternate from the set, ie agent A_i and A_j arrive at A_j's selection of alternate. An iterative process is repeated until all group members arrive at single decision based on overall trust as show in Fig. 3. This trust based cooperation enhances the group consensus and result in selection of best alternate. The uncertainty present in attributes of MCDM decision for a given task is modeled by evaluation of domain trust in our trust computational model [1]. It is further improved through learning to trust recommenders and presented in next section.

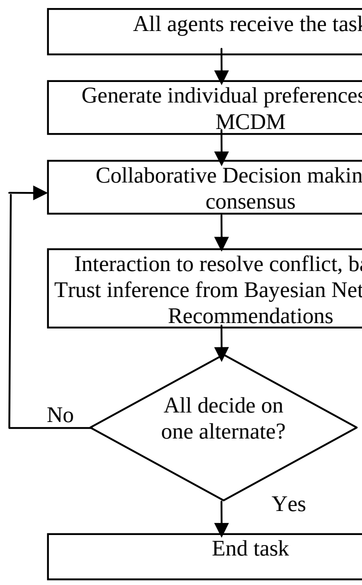

Fig. 3 Consensus based on Trust for cooperation

IV. LEARNING

Learning and the socialization processes primarily shape the trust. If most of the people within the social environment are reliable and trustworthy, it will result in positive outcome.

We have proposed reinforcement learning based on agent's recommendation and trust. Trust learning is a crucial aspect of information exchange in MAS. The learning component in Fig. 1 receives direct trust and recommendations from Behavioral process. When agent A_i interacts with agent A_j, it updates its trust on agent A_j. While agent A_i updates trust on A_j, it also updates trust on other agents who are providing recommendations for agent A_j. If the current interaction of agent Ai with agent A_j is satisfying, and recommendation from agent A_k about A_j is also confirming, agent A_i updates its trust in the recommending agent A_k by using the reinforcement learning as in equation 3.

$$T_{ik(t+1)} = \beta * T_{ik(t)} + (1- \beta) * E_v \quad (3)$$

Where $T_{ik(t+1)}$ denotes the new trust value of agent A_i on agent A_k and $T_{ik(t)}$ denotes the old trust value. β denotes the learning rate, which is a real number between [0 ,1] interval. E_v is the new evidence value dependent on PR. The value of PR is based on individual recommendation sent by each agent as shown in Table II. The individual recommendation ($P[R_k^0 / GR]$ or $P[R_k^1 / GR]$) sent by other agents about agent A_j is PR.

TABLE II
INDIVIDUAL RECOMMENDATION RECEIVED BY AGENT A_1 ABOUT A_2 FROM OTHER AGENTS

Agent	Recommender Sent value PR
A_3	.6
A_4	.7
A_5	.3

An agent learns to trust recommenders by evaluating its recommendation as per equation 3. This learning helps an agent to build trust faster in future interactions.

A. Analysis of Behavior of Agents

Learning the behavior of an agent is very important in organizational level. The conflicting behavior or inconsistent behavior in given context or domain largely helps in further team allocation or group work. Hence by embedding the trust computational model as a part of CSCW greatly help the organization in identifying trusting behavior of an agent in the given domain.

Once the probabilistic recommendation is received by an agent A_i, evidences are observed and agent Ai updates its trust value with agent A_j and recommenders of agent A_j. The computation and prediction of recommendation values computed in equation 1 reveals several outcome of group consensus protocol. Analysis of these values reveals whether an agent's behavior is inconsistent or trustworthy or conflicting. The results are analyzed based on R= 0.5 as recommendation threshold and is shown in Table III.

TABLE III
RECOMMENDATION RECEIVED BY AGENT AND ITS RANGE

R	***Value***
High	0.51 to 1
Low	0 to 0.5

An agent's sent recommendation R and General Reputation GR is matching as in algorithm of Fig. 4, then that agent behavior (observed over several task and domains) is consistent. If R and GR are contrast then agent is behaving in conflicting manner. If agent behavior changes many times over several tasks, it is considered as inconsistent behavior (over several task if agent's value of R is changing several times crossing threshold, then agent's behavior is inconsistent in that domain.

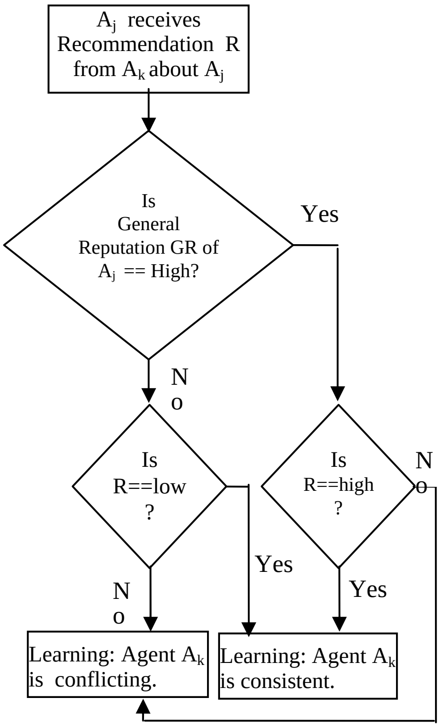

Fig. 4 Deciding behavior of agents based on R and GR values

Our experimental work presented in next section shows the advantage of trust based method compared to voting technique for alternate selection.

V. IMPLEMENTATION AND EXPERIMENTAL WORK

For our experimental work we have considered the application of new project selection in an organization. Project Selection is the process of evaluating individual projects, to choose the right project based on an analysis so that the objectives of the company will be achieved. It involves a thorough analysis including the most important financial aspect to determine the best project among all the alternatives. A chat server integrated with DEXi Multi Criteria Decision Making tool [7] to generate different alternates.

Our experiments involve 5 agents. Each agent exchange trust value, recommendations after every 10 interactions with other agents. To simplify our work we have assumed equal priority for w_1 and w_2 and are set to w_1= w_2 =0.5. The prior probabilities for DT and R are uniformly set for each agent as 0.2. Total number of interactions are 800 and General Reputation GR for A_1 =0.4, A_2 =0.8, A_3 =0.85, A_4=0.9 and A_5 =0.9, Learning rate β =0.5.

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A. Results

The team of agents is presented with a task to generate set of alternate solution from which agents have to arrive at consensus on one best alternate. Some projects have high uncertainty for example R&D cost and operating cost. Agents have different preferences over these values. Agents generate different alternatives as in Table III. Out of these five alternatives, one project is to be selected by the team during collaboration.

TABLE IV
DIFFERENT ALTERNATES GENERATED BY EXPERTS / AGENTS

Criteria	X_1	X_2	X_3	X_4	X_5
Equipment cost	2500	1500	2500	1750	2000
Engineering Cost	3000	2500	3000	2500	2500
Construction cost	1500	750	1100	1200	1100
Material Cost	1200	1250	1300	1300	1300
Owner's Cost	1500	1200	1200	1200	1500

Experiment 1

We have compared voting method and our trust based decision and trust with learning for project selection application. In voting, agents select alternate X_1, X_2, X_3, X_4 and X_5 based on majority. In our trust model, agents select alternate based on overall trust computation. Results shows voting method do not have any improvement over number of interactions whereas trust based method shows improved group consensus over number of interactions between agents. The trust learning based on recommendations further improves computation and group consensus as in figure 5. As the recommendations from different agents are received by an agent it learns and updates trust value. The threshold =0.5 is considered for trust learning evidence. Trust levels updating takes lesser interactions compared to only trust computation without learning.

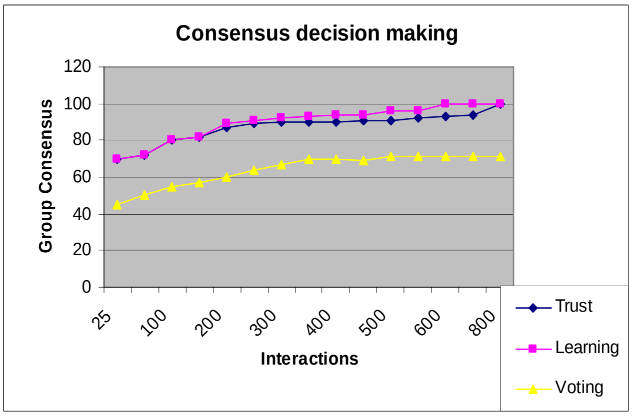

Fig. 5 Improved consensus with learning

The trust values computed by an agent for cooperative decision making are given in Fig. 6. Agent A_1's computation of trust values reveal that consensus is achieved only after trusting behavior of an agent is above threshold (0.5). As number of interactions increase, based on recommendation values, and learning to trust other agent, the overall trust varies as shown in Fig. 6.

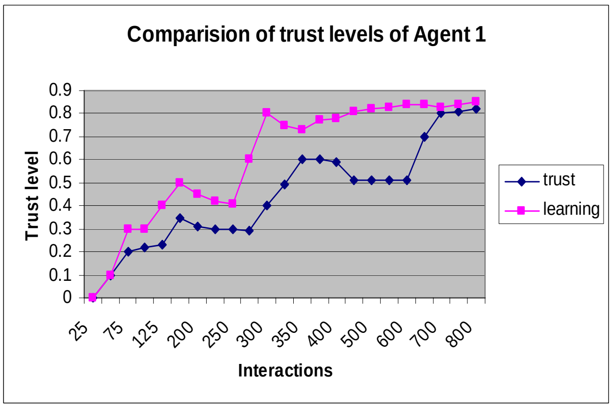

Fig. 6 Trust level of an agent with learning from recommendations

Experiment 2

As recommendations from an agent are varied over number of interactions, an agent learns about the recommender's behavior. These kinds of recordings help an organization in analyzing an agent's inconsistent behavior on decision of work group formation in a given context or domain. Fig. 7 shows behavior of recommending agent during different tasks and domain d. We have considered agent with high General Reputation GR = 0.9 and learning rate = 0.5. Depending on the values of R, agent behavior is classified as consistent, conflicting and inconsistent in a given domain. 400 interactions are considered for each task.

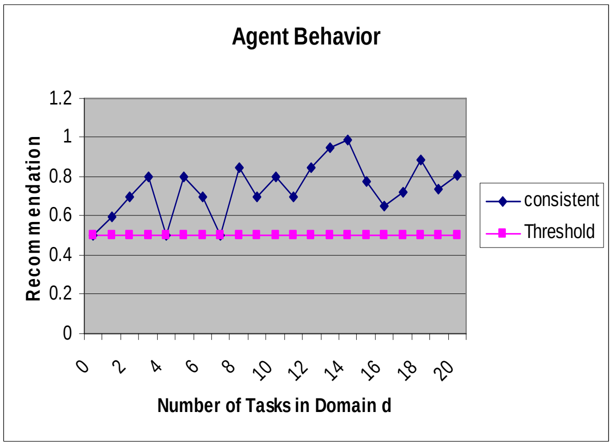

Fig. 7a Recommendation from other agents about Agent A5 with GR=0.9

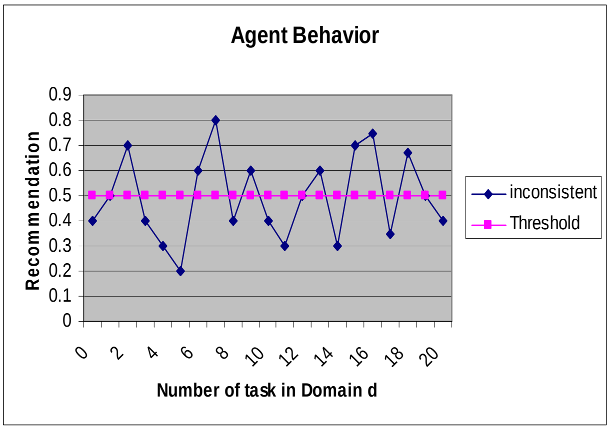

Fig. 7b Recommendation from other agents about Agent A5 with GR=0.9

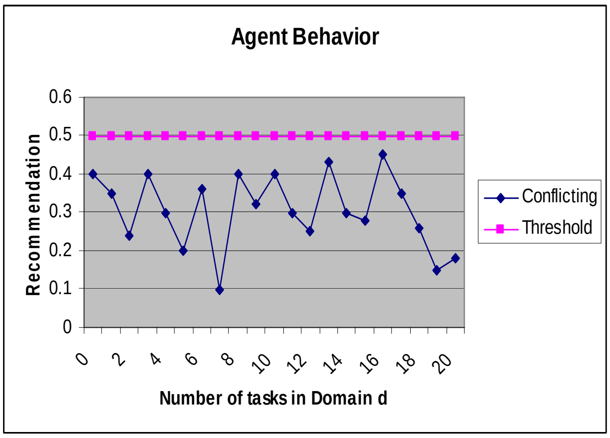

Fig. 7c Recommendation from other agents about Agent A5 with GR=0.9

VI. Conclusion

Social network analysis is the study of social relationships between individuals in a society. Social network analysis emerged as a set of methods for the analysis of social structures. Social issues such as trust and reputation are key factors in Virtual Organization as Face-to-face communication is not always possible. In this paper, we have emphasized social aspects of CSCW such as trust between group members for best alternate selection from a given set of alternate solutions. We have provided a model of trusting behavior and learning in collaborating agent framework for representing, reasoning about group activity in Virtual Organization scenario. This trust model allows team members or experts to interact, collaborate and perform decision making. We verify our model in a multi-agent simulation where the agents in the community learn to identify trustworthy members, inconsistent behavior and conflicting behavior. This behavioral learning is very helpful in future team formation for problem solving in an organization.

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