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MODELING SOCIAL NORMS IN MULTIAGENT SYSTEMS

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Abstract

Social norms are cultural phenomena that naturally emerge in human societies and help prescribe and proscribe normative patterns of behavior. In recent times, the discipline of multiagent systems has been modeling social norms in artificial society of agents. This paper reviews norms in multiagent systems and then offers exploration of a series of norms in a simulated urban traffic setting. Using game theoretic concepts we define and offer an account of norm stability. Particularly in small groups, for the norm of cooperation to evolve and be *stable*, a relatively small number of individuals with cooperative attitude are needed. In contrast, in larger populations, to achieve stability larger proportion of cooperating individuals are required.

Keywords: business policy, decision making processes, decision support systems, decision outcome measures, decision process measures, management support systems, multiagent systems

I. INTRODUCTION

Multiagent system's (MAS) research is useful in a number of application areas. The need for automation in the decision making of mission-critical systems such as space exploration and for designing complex systems such as distributed operating systems and computer networks has accelerated the research in multiagent systems. Agents in the multiagent systems are considered to be intelligent because they posses a high degree of autonomy and can make decisions by perceiving the environment in which they reside. Several models for MAS have been explored and presented in recent years (Castelfranchi, 1995; Rao and Georgeff 1995; Beavers and Hexmoor 2003). One of them includes adding norms to agent architecture (Castelfranchi, 1995; Shoham and Tennenholtz, 1992; Rao and Georgeff 1995). In this paper, the effects of norms on agent architecture are discussed. In the following sections, we give a brief introduction to agents and multiagent systems as well as application of norms in multiagent systems. Next we review relevant literature. We follow this by a description of our implementation of norm strategies and efficacy explorations of norms. Experimental results, conclusions and future work are offered in the remaining sections.

Agents and Multiagent Systems

The notion of an agent spans a large number of disciplines and has a number of definitions in general and in the Artificial Intelligence (AI) community. There has been significant debate on the definition of an agent in the MAS community and still there is no commonly agreed-upon definition. Various definitions are given by different researchers which are relevant in a narrow field or a subset of application domains.

Wooldridge and Jennings offer this definition: “An agent is a hardware or more usually software entity that enjoys the properties such as autonomy, social ability, reactivity and pro-activeness” (Wooldridge and Jennings, 1995). The following briefly outlines these properties.

- **Autonomy**: Agents operate in an environment without direct intervention of humans or others, and have nontrivial control over their actions and internal states.
- **Social ability**: Agents interact with other agents (and possibly humans) via a style of agent-communication language.
- **Reactivity**: Agents perceive the environment in which they reside and respond in a timely fashion to changes that occur.
- **Pro-activeness**: agents do not simply act in response to their environment; they are able to exhibit goal-directed behavior by taking initiative.

These are a few of the properties that differentiate a computer program from an agent.

Multiagent Systems: Multiagent systems evolved as a methodical solution to large, complex and distributed problems where single agent control is either not feasible or restricted by the amount of resources it may posses. There are also risks involved in using a centralized control system. This has led to the new conceptualization of multiple agent solutions. The requirement of multiple agents to work collectively on large problems can be visualized as modules in object-oriented programming. Each agent is assigned to a particular sub-problem from the main problem and each part of the problem is required to be as independent as possible from other parts but this is not necessary. The more independent a sub-problem becomes the more autonomous an agent must be. These independent agents need to coordinate and share information to bring about a solution to the problem. Prof. Katia Sycara describes some of the characteristics of MAS in (Sycara, 1998):

- Each agent has incomplete information of its environment and also does not posses capability to solve the entire problem; thus has a limited viewpoint.
- There is no system global control.
- Data is decentralized.
- Computation is asynchronous.

Each agent in a multiagent system is considered rational and autonomous in making decisions for improving its individual benefit. Several models were introduced to an agent design. The BDI approach depicted in Figure 1 has been the most prominent and sustaining. BDI stands for Beliefs, Desire and Intentions. BDI approach to agent design to rational agents was introduced in (Castelfranchi, 1995; Rao and Georgeff 1995).

- **Beliefs** are the set of information that an agent has at certain time about the environment in which it resides. They are the knowledge set that an agent holds about its environment.
- **Desires** are long-term goals that the agent tries to achieve. These desires may change.
- **Intentions** are the agent's short-term goals or the goals that an agent is currently trying to achieve.

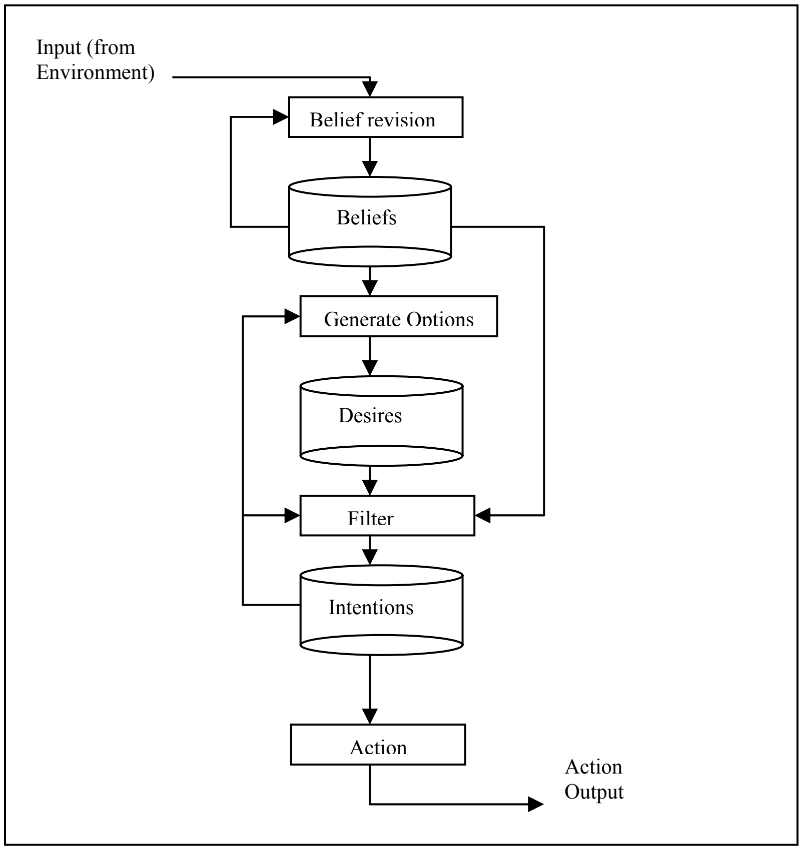

Figure 1. A Schematic Model of a BDI agent

Multiagent systems are developed to address complex systems where a human being cannot predict beforehand its behavior at a particular instance. This leads to the desirability of coordination and agent autonomy in multiagent systems and their adaptability to the changing environment. Agents need to coordinate to achieve their individual goals and common goals. One possible solution to the coordination problem is using norms. Hexmoor and Beavers discussed extending the traditional BDI (Castelfranchi, 1995; Rao and Georgeff 1995) approach of an agent to include obligations and norms (Beavers and Hexmoor, 2002; Lacey, Hexmoor, and Beavers 2002). Hexmoor and Lacey showed that adding norms to agent modeling enhanced system performance (Lacey and Hexmoor, 2003). They showed that multiagent systems that adopt norms according to changes in the environment perform well over the agents who rigidly follow only one norm.

Norms in Social Agents

Application of social theories to multiagent systems has provided useful models. Adding models of norms to social agents is a fairly recent development in multiagent systems research (Castelfranchi 1995; Shoham and Tennenholtz 1992; Rao and Georgeff, 1995 Boman, 1999). Norms in social science theory is a well-known concept and extensive research is available in this area. Carter, et al. argue that norm models for agents working in a social group enable agents to resolve conflicts and reduce complexity, thereby bringing about social coherence among agents (Carter, Ghorbani, and Spencer, 2001). A norm has several definitions. One definition taken from the Webster dictionary defines a norm as “a principle of right of action binding upon the members of a group and serving to guide, control, or regulate proper and acceptable behavior” (www.webster.com). Norms also have different definitions in different areas of study such as social science, game theory, psychology and legal theory. Cristina Bicchieri defines a social norm in general as:

A social norm (N) in a population (P) can be defined as a function of beliefs and preferences of the members of P if the following conditions hold:

- Almost every member of P prefers to conform to N on the condition that almost everyone else conforms too.
- Almost every member of P believes that almost every other member of P conforms to N (Bicchieri, 1990).

Multiagent researchers have a definition of their own. In (Rao and Georgeff, 1995) Rao and Georgeff offered a few different views of norms in the multiagent scenario.

- Norms as obligations.
- Norms as goals or objectives, this can be closely related to desires in BDI architecture.
- Norms as constraints on behavior.

In most normative multiagent systems including our discussion, norms are considered as constraints on behavior. They constitute a set of rules or constraints that an agent should abide by in autonomous decision-making. Agents resolving norm adherence based on sanctions and rewards is discussed by Conte and Castelfranchi (Conte and Castelfranchi, 2000). In this paper they argue that *incentive based rational deciders* try to abide by the norms based on evaluating their utility. Norms in agents thus forms an important model for use in an agent in multiagent systems. A normative agent is an autonomous agent whose behavior is shaped by the norms it must comply with, and it decides based on its goals whether to adopt a norm or dismiss it. The norm set that an agent considers for adoption depends on the environment in which it resides. An agent might be a member of a small organization or it might be a member of several organizations. Depending on the membership and its individual desires and intentions an agent is confronted by a set of norms. Prototypical dynamics of norms in a multiagent environment are shown in Figure 2. An agent inherits a set of norms by being part of the society. Based on the situation and the society that it is part of, an agent has to strictly abide by some norms and for other norms it has to consider an adoption strategy to decide whether to comply. In Figure 2, the *issue* stage is shown to be the starting point in the dynamics of norms. Initially, a society identifies the possible set of prevailing norms and propagates them to individuals in the society. During the adoption stage, an agent forms a personal representation of norms. Once an agent internalizes all the potential norms by being part of different societies weighted against individual goals, the agent commits to a subset of norms. Agents account for the consequences of dismissing a norm. The norm that an agent complies with affects other members of the group, so an agent has to consider other agent's expectations and well being in its deliberations. Norms are enforced by sanctions when an agent fails to comply as well as by enticements in the form of social capital gained as a reward for conformance.

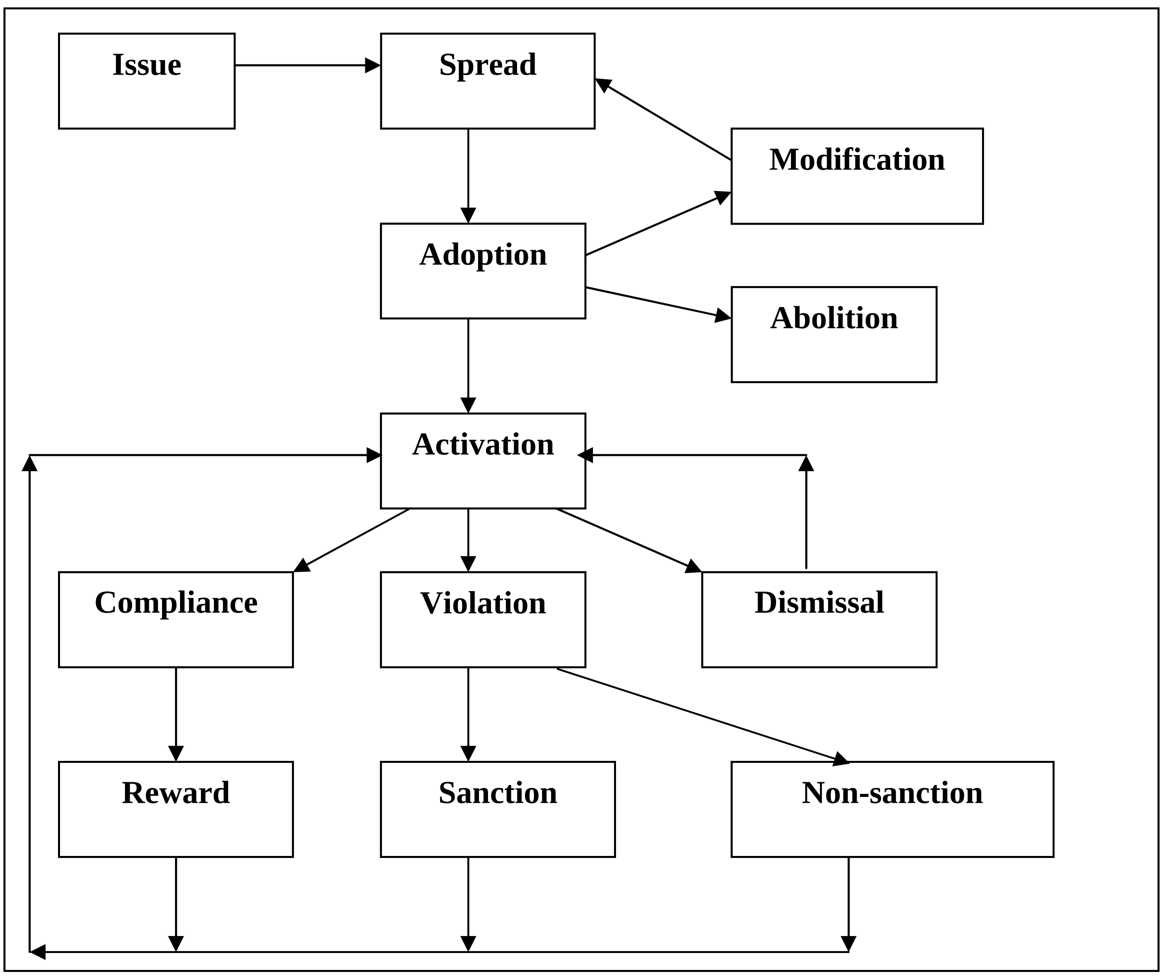

Figure 2. Dynamics of Norms (Adapted from (López and Luck, 2004))

Models of agent norms are useful in many arenas; in this discussion, strategies themselves are considered as norms. Consider a situation in a grid-based computing environment, where several agents are trying to use different resources on the grid like information, computing power, etc.

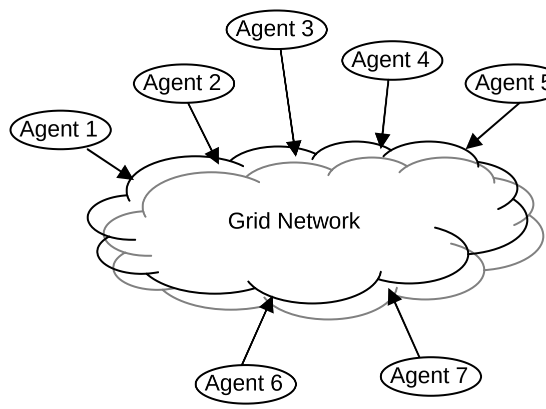

Figure 3. Agents in a grid-based network

In this example as depicted in Figure 3, let's envision we might enforce a norm that "an agent cannot use more than two resources at the same time". Considered as highly autonomous, the agent can choose either to cooperate (C) or to defect (D). If all the agents in the system choose to defect then there would be a possible overload on the network and this may lead the grid-system to completely fail to respond. This situation is not desirable. If on the other hand, this norm was enforced in the system through sanctions and rewards, there would be a possibility for cooperation and a functioning grid. Finding the payoffs for cooperation and defection depends on the situation and different parameters like the amount of time the agent has to wait to gain the resource if it cooperates, the cost of request, and the cost of processing, etc. Once the payoffs are decided, the next stage is to find the strategies that yield better utilities for agents as well as to improve the total system performance. A game theoretic view on how cooperation among agent can occur given the payoffs is discussed in the next section.

Norms in Game theory

In Rational Choice Theory, the emergence of social norms is due to the fact that abiding by norms yield benefits to individual agents as well as to groups. Game theory is a sub branch of Rational Choice Theory that deals with social interactions among rational agents. In game theory, cooperative behavior can be viewed as a general equivalent to any norm. Nash Equilibrium is the situation in games involving two or more players such that no player may benefit by changing strategies unless there is a change in strategy of the opponent (Nash, 1951). If there is such equilibrium, then rational agents would automatically choose to stay in the equilibrium; otherwise, one of the players gets exploited by other members of the population. Let us consider a game that offers Nash Equilibrium as the dominant strategy. Here a player always chooses a strategy that is more beneficial no matter what the opponent strategy is. The following example of game illustrates this.

Player 2

Player 1		Cooperate	Defect
	Cooperate	2,2	5,0
	Defect	0,1	1,2

Game 1

Table 1. Payoff Matrix for Game 1

In the game with a payoff matrix shown in the table 1, in each cell a pair of payoffs is illustrated. The First payoff shown is for row player i.e. Player 1 in this case. Here Player

1 always chooses to cooperate, not considering what strategy the other player chooses, since he always achieves better payoff by cooperating. Player 1 has a dominant strategy. Having a dominant strategy in a game contradicts the first definition of norm given earlier, since player one always chooses to cooperate and his choice does not depend on what he expects player two will choose. Ullman say that in games like this, where there exists a dominant strategy, emergence of norms is not possible (Ullman-Margalit 1977). Ullman gives a game theoretic view on norms. He describes that a norm is broadly defined as equilibrium. Let us examine another example where there are more than one strategy equilibriums: payoffs for this example are given in table 2.

		left	right
Player 1	left	3,3	1,1
	right	1,1	3,3

Game 2

Table 2. Payoff Matrix for Game 2.

Consider a situation where, in a city there are no traffic rules and commuters are free to choose to either drive on the left or right side of streets. If two agents enter the city and, they have to choose to commute on the left or right. If Player 1 chooses to go on the left, then Player 2 would be better off choosing the left from the pay-off matrix. On the other hand, if Player 1 chooses to go on the right when Player 2 chooses the left, then there would be a collision resulting in diminished payoffs for both agents. Therefore, Player 2 would now choose right for which it yields a better payoff. As you can see in this game, there are two independent strategy equilibriums; namely both drive on the left and both drive on the right.

Emergence of Norms of Cooperation

Player 2

Player 1

	C	D
C	3	0
D	5	1

Table 3. Payoff Matrix. C-Cooperation, D-defection.

Consider a prisoner's dilemma like situation with a payoff table associated as shown in table 3. Assume that the payoff table is symmetric i.e., the first player who makes a move is considered as Player 1 (row player). Assume that players play each other only one time. Player 1, being rational, chooses to defect. This leads to defection choice for rational Player 2. In this game, both players choosing to defect is the optimal strategy; a Nash equilibrium. If instead, the two players are involved in repeated play of the same game, then rational players would try to adopt a different strategy by learning about the strategy of the opponent. In this case, the optimal strategy leading to an equilibrium that would yield more individual utility to both players is conditional cooperation, also known as tit for tat. If, on the first round, player one cooperates for the first time, the other would opt to defect. Knowing this, in the next round, Player 1 chooses to defect, sending a message to the opponent that he is a conditional cooperator. In the next round of play, he chooses to cooperate, this time knowing that he would be rewarded for the cooperation when engaged in the next round of play. If this game is repeated n-times, and the players are to choose from either unilateral defection or tit-for-tat strategy then cumulative utilities earned by both players is as follows:

- If a defector is confronted with another defector then in n-rounds the cumulative utility earned by either player is n. Let it be represented by Δ_{DD}.
- If a defector is confronted with a tit-for-tat strategist then the cumulative utility earned by defector is n+4. This is so because the cooperative behavior of tit-for-tatter can only be exploited in the first round, and thus gaining 5 in the first round. From second round onward they both defect, leading to a total utility of n+4 for the defector. Let the utility of defector in this case be represented by Δ_{DT}.
- On the other hand, the gain for tit for tatter is n-1 since his co-operative player is being exploited in the first round. Let the utility of tit-for tatter be represented by Δ_{TD}.
- If a tit for tatter is confronted against another tit for tatter then the total payoff associated with either player is 2n.

$$\Delta_{TT} = 2n \qquad \Delta_{TD} = n-1$$

$$\Delta_{DD} = n \qquad \Delta_{DT} = n+4$$

Thus the payoff's shown above indicate that it is better to be a conditional co-operator. From the payoffs it can also be interpreted that cooperation can evolve among a population of selfish agents if there are more interactions among agents. If in a population of more than two players, one interesting scenario is to notice whether the existing strategy is *stable* against mutants (newly introduced players) entering the current population. If there are two strategies existing in the population, then the question of focus is whether the existing strategy *stable* or if one strategy dominates the other over time.

II. Literature Review

Multiagent systems with agent models involving norms have become common in a number of projects and simulations. This section gives a brief background on norms in social theory and normative agent systems. Section 2.3 describes projects and simulations where norms in agents are an important aspect of research. Application of normative agents in multiagent systems varies from a norm as a simple constraint on agent behavior to complex norm revision and adaptation, dynamically involving agent autonomy, trust etc.

Norms in social theory

In social science research, norms are considered as responsible for regulating social behavior of individuals. They prescribe how to interact and resolve issues in conflicting circumstances. Emile Durkheim discusses how norms are effective when agents interact with complete strangers (Durkheim, 1984). She argues that it is hard to explain how interactions can take place between strangers without norms. Norms in legal theory are designed by deliberation (are saved in proper written form) and are enforced through strict sanctions by enforcement agencies or special bureaucracy (Horne, 2001). Norms in social theory emerge spontaneously rather than deliberately planned as in the case of legal theory. There are several views on social norms by different researchers. Some view norms as the means agents use to interpret situations and take action accordingly. On the other hand, game theorists view cooperative behavior as a general equivalent to any norm. Norms propel agents to consider social situations in their decision-making rather than acting selfishly.

Tuomela, et al., summarized that social norms can be broadly classified into two groups, namely r-norms and s-norms (Tuomela and Bonnevier-Tuomela, 1995; Tuomela, 2000). r-norms stand for rule-like norms and s-norms for proper social norms. Authority or a set of agents representing a group forms rules. While r-norms are based on agreement making, s-norms are based on mutual cooperation. Apart from these, there are personal norms and potential social norms. Potential social norms fall in between social norms and personal norms. Social responsiveness is not considered in the case of potential social norms. Within potential social norms there are two other kinds of norms namely moral norms (m-norms) and prudential norms (p-norms). Moral norms are created based on an agent's individual conscience whereas prudential norms are based on rationality of an agent. All norms form a critical part of an agent's decision-making process.

For norms to be efficient there should be some means of enforcement. Otherwise, they serve merely as assertions of ideals (Horne, 2001). Different views are given in answering the question of what is it that makes norms effective. Some say that norms must be internalized i.e., agents must themselves apply rewards or sanctions for their own decision-making (Durkheim, 1951; Coleman, 1990). This means that an agent follows a norm because it chooses to. While some believe that internalization as an enforcement mechanism, others believe that sanctions must be exercised externally. On this view "norms are ordinarily enforced by sanctions, which are either rewards for carrying out those actions regarded as correct or punishments for carrying out those actions regarded as incorrect" (Durkheim, 1951; Blake and Davis, 1964). Even those who rely heavily on the idea of internalization still recognize the importance of additional resources of the environment.

Normative Agent Systems

The importance of obligations in organizations and social situations is discussed by Castelfranchi (Castelfranchi, 1995). Yoav Shoham in his paper discussed usefulness of social laws for artificial agent societies. In his discussion he deliberates about norms in social groups as an important aspect that needed to be applied to agents (Shoham and Tennenholtz, 1992). Shoham also proposes an agent-oriented language (AOP) where the obligations are treated at the agent level, and the obligations at the social level are ignored (Shoham, 1993).

Extensive work is carried out by Harko Verhagen on agent norms (Verhagen, 2000; Verhagen, 1998). In his doctoral thesis, Verhagen discusses norms in artificial agents (Verhagen, 2000). He discusses norms in social, legal, and various other branches of social theory and deliberates how the models evolved there can be adopted to multiagent systems and agent based social simulations. He concludes that learning of norms can be divided into two types; how norms emerge and how norms are accepted. Verhagen discussed how learning of norms takes place in Agents (Verhagen, 1999). Verhagen also discussed several issues about how individual agents select the set of norms at the start of simulation, and studied the effect of autonomy on the initial norm set.

Applications

Multiagent systems are applicable in various fields like E-commerce, Large Distributed Networks, Military and Educational simulations, and Robotics to name a few areas.

Large projects that need extensive modularization of the process and the problem of unpredictable system state and complexity urge the requirement of independent autonomous agents to work together. This section introduces and refers to some important and relevant areas of research in which normative multiagent systems and MAS in general are used.

Multiagent systems in business applications are effective because businesses deal with continuous input of vast and varying information and maintenance of distributed databases over Intra and Internets (Chavez and Kasbah, 1996; Carter, Ghorbani, and Spencer, 2001). Agent technology is being effectively used in online bidding, auctions, and search engines. An agent can represent various roles such as User Preference Agents, Information Broker Agents, Buyer Agents, and Seller Agents etc. Social awareness of agent is one of the main research concerns in modeling agents in e-commerce. Social adeptness of agents involves issue of negotiation, norms, trust, role adoption etc. Trust and Negotiation form important parts of social agents; agents need to cooperate and organize their activities to achieve their individual goals as well as collective goals (Rahman and Hexmoor, 2004; Beavers and Hexmoor, 2003).

Agent based Community-Oriented (Retrieval | Routing) Network (ACORN) developed for use in various applications such as E-mail, search engines, B2B (business to business) and B2C (business to consumer) applications (Marsh and Masrour, 1997). In ACORN, each agent is autonomous or semi-autonomous representing a separate piece of information. The information that an agent represents can be a file, a link, an image, a movie, a document, etc. Each agent carries with it information such as where it originated, the owner, and information about its community. Since agents are considered autonomous and socially aware these agents and learn and accumulate or change the information it carries with it dynamically as it moves around the network.

Lloyd, et. al., proposed norm aware agent architecture for operating Ad Hoc Networks (Kamara, Pitt, and Sergot, 2004). They argue that Ad Hoc Networks (AHN) that are characterized by spontaneous communications structure and self-organizing capability are suitable for agent-based approach. They propose a norm aware agent model and put forth the issues concerned with such an agent based approach. They considered AHN as like agent-based society and as a type of norm-governed system. The issues concerned with this model that is deliberated as the architecture for social agents are communications protocols for coordination, and management language for social order.

Active Network Distributed Open Infrastructure Development (ANDRIOD) is an ongoing project at the University College of London (Liabotis, Prnjat, and Sacks, 2001). This project aims at finding the feasibility of providing a managed, scalable, programmable network infrastructure capable of supporting the future needs of the Information Society. Multiagent System for network Resource Reliability (MASRR) is another project that is using multiagent approach to resource management and reliability (Gasch, 2004; Jones and Carpenter, 2002). The authors aim to build decentralized agent based architecture for maintenance of huge networks such as the Internet that is made of several heterogeneous networks connected together. Resource allocation (dynamically adapt to continuous change in network configuration), reliability, scalability, security are a few of the important issues of focus in developing such systems.

Agent based approaches to grid based computing is also one of the areas that is gaining focus. There have been several workshops held at the IEEE such as the IEEE International Symposium on Cluster Computing and the Grid calling for papers and present about agent based approach to grid computing.

An Agent based approach to complex health care tasks is proving to be useful due to the natural ability of multiagent systems to adapt to new situations (Vázquez-Salceda, 2004; Nealon and Moreno, 2003). The normative nature of agents in multiagent systems is particularly more suitable because of various regulations of health care based on region, country, geographical context, etc. Multiagent systems can be applied in fields like surgical simulators, distribution of human tissues, organ allocation, patient scheduling, information, access, etc.

Authors in (Vázquez-Salceda and Dignum, 2003; Vázquez-Salceda, Cortés, et al, 2003) discuss electronic institutions based on institutions in social settings. Constraints or rules in human interactions of a society are argued to be institutions (North, 1990). Vazquez, et al., define an institution as a set of possibly interdependent norms and argue that using institutions simplifies interaction and creates confidence. Moreno argues that organ allocation is a complex process (Nealon, Moreno, 2003). Finding the right recipient when a new organ is available is a difficult and complex process since each hospital in a country has its own information about patients. Organizing this information and perfectly coordinating organ allocation process in time critical situations require more than just one central operating environment. Vazquez developed a formalization of a model based on ISLANDER for distribution of human tissues and organ allocation process (Esteva, Padget and Sierra, 2001). Norms, privacy and trust are some of the issues to deal-with in such agent-based formalizations.

III. Approach and Implemented Simulation

In this section a description of traffic grid simulation model is given. A set of definitions of the variables in the model is presented here. In the next section an approach to efficacy of norm adoption strategy based on Game Theory and Bicchieri's work is discussed.

We tested norm adoption strategies and efficacy of norm strategy using a simulated city traffic scenario that is based on agents delivering goods in a city. The traffic grid simulation is implemented using the Java programming language. A snapshot of the simulation grid is show in the Figure 4. There are four roads; namely, R1, R2, R3 and R4. Two of the roads are in the east-west direction and two of them are in north-south direction. The intersections of the roads are junctions. There are four junctions; namely, J1, J2, J3 and J4. The traffic at each junction is controlled by traffic signals. The traffic signals are also shown the Figure 4.

The set of traffic signals are green, red and yellow. The traffic signal yellow is provided for the traffic that is in junction to safely pass through the junction with out any collision.

There are eight terminals; namely, T1, T2…T8. These terminals are the places where agents start and end their journeys. Lacey and Hexmoor implemented a similar scenario using SICStus Prolog and Tcl/Tk library (Carlsson and Wid'en, 1993). The present scenario implemented in Java is easier to use and configure. The graphical interface has enhanced features to change various parameters at run time. The simulation is extensible, for instance new configurations can be added to agent models.

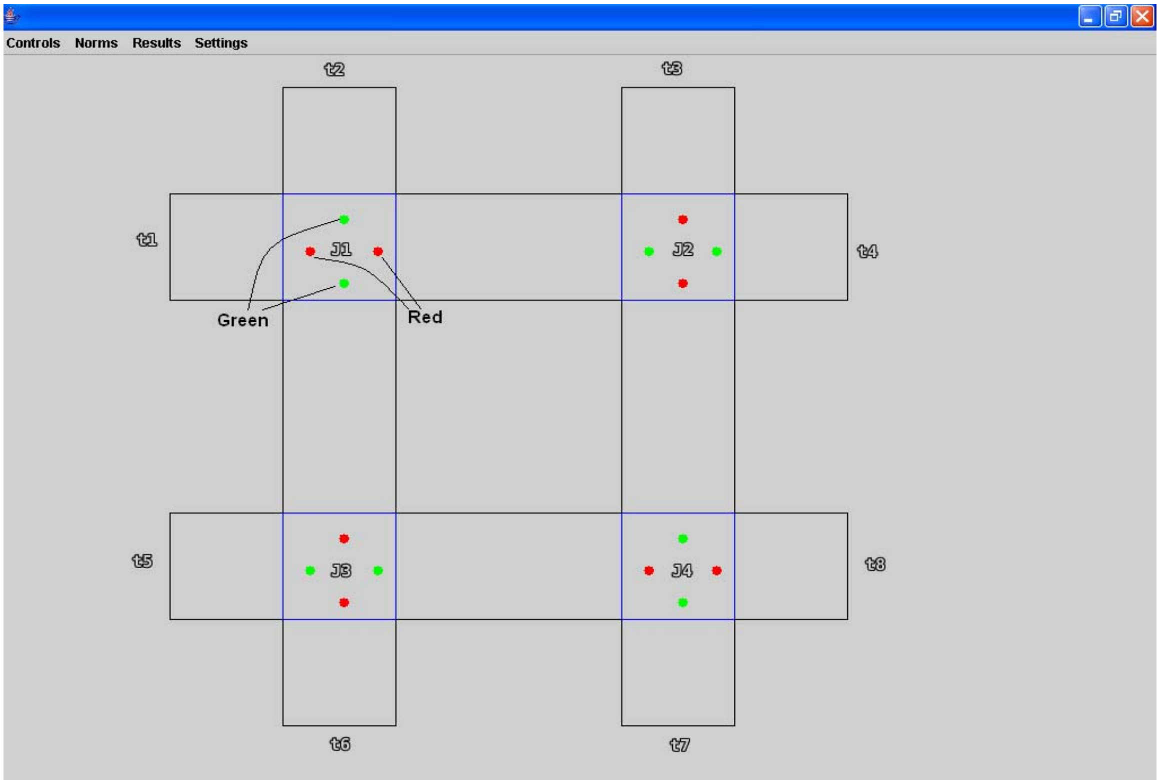

Figure 4. A typical snapshot of Traffic Grid Simulation Panel

Traffic Grid Model

- The data representing state of the environment denoted by *Traffic Grid Data* at a time *t* consists of agents, junctions, terminals, roads, accidents etc. each of which in turn is a sub-data set representing various internal state values at a particular time period *t*.

$$Traffic\ Grid\ Data = \{A, J, T, R, A_C, t, S_A, N\}$$

- The number of agents in the simulation, denoted by the *number of agents- n(A),* is a number greater that one.

- The variable R represents roads in the grid setting. The data set for R is constant since the roads are stable. R represents 2 sets of roads, two are horizontal spanning from east to west and 2 are in vertical direction spanning for north to south. R also contains the data about spatial orientation of the roads i.e., their position in two-dimensional (2D) space.

- The variable J represents junctions. A Junction is an intersection of a pair of roads. There are four junctions namely J1, J2, J3, J4. Each junction has signals to control North-South and Each-West bound traffic. At any time t only either North-South or East-West bound lights are green. J also contains the data about spatial orientation of each junction i.e., their position in 2D space

- The variable T represents terminals. Terminal is the starting point where agents start and end their journey. There are eight terminals naming T1, T2…T8 in the Grid. T also contains the data about spatial orientation of each terminal (where in the terminal to start to end) i.e., their position in 2D space.

- Variable S_A represents system average at time t. The system average is calculated as average of the total number of trip made by all the agents together.

$$S_A = (\sum_i \text{ No.of Trips(Ai)})/ n(A)$$

- A_C contains the data about the number of accidents in the time slice t and the cumulative accidents unto *t.*

- States, denoted S, is a set of possible moves or states that an agent can be in at particular time.
    1. Move to next position
        - (i) Move North
        - (ii) Move South
        - (iii) Move East
        - (iv) Move West
    2. Wait for traffic signal if cooperating
    3. In Accident state (wait for certain specified time)
    4. Completed state if an assigned target is reached
    5. Get new target if current assigned target completed
    6. Stop if no new targets available

- The Position of an Agent A_i in the Grid, denoted by a function *position* (A_i,t), is a point (rectangle of some dimension) in 2 dimensional space.

- The current time-step, denoted by *t,* is the number of turns that have elapsed since the beginning of the simulation.

To reduce complexity the following assumptions are made in the simulation. we have assumed that there are only head on collisions. i.e., there will be no collisions between two vehicles (agents) which are traveling in the same direction. Here we assume that there are infinite parallel lanes in any direction, this is not shown in the simulation but assumed.

- The data set for each agent Ai of the set A can be represented by the following model

  Ai = <S, N, P, N_s>

Here S represents current status of agent as defined in earlier, N_s represents the norm strategy that the agent is currently following, N represents the number of trips the agent Ai has currently completed and P is the position of the agent as defined earlier. There are two norms in the set N in the traffic grid. They are to cooperate (C) and to defect (D). When an agent reaches a junction it has to decide to whether to stop for or not if there is a red signal. The course of action that it chooses depends on the norm strategy it follows at that particular time *t.* When an agent wants to adopt the norm to cooperate, the agent has to stop for all the traffic signals i.e., stop for a specified amount of time if there is a red signal. If the agent wants to adopt cooperative norm the agent might degrade its performance by stopping for all signals even though there may not be a possible collision. When an agent wants to adopt the norm to defect, the agent ignores all the traffic rules. If an agent ignores the traffic rules there may be a possibility of an accident involving an agent who is actually following the rules. This not only leads to decrease in the performance of the individual but also there will be loss performance of total system. The top level system simulator loop is shown in Figure 5 and an agent top level loop is shown in Figure 6.

1. Assign initialize targets for all agents.
2. Send Grid data to agents.
3. Run agent algorithm for each agent.
4. Determine updated position for each agent, update accidents list and performance of the system.
5. Run Graphical Simulation panel to show new positions of the agents.
6. Update Graph Data.

Figure 5. The simulator top-level loop

1. Analyze new traffic grid data and revise beliefs about the environment and about all agents in the system.
2. Get new target if there is no target assigned
3. Compute the next position if not near a junction
4. If near a junction check for lights and generate state space and determine plan according to norm strategy.
5. If needed generate message to send to other agents and request simulator to deliver the message.

Figure 6. An agent top-level loop

Norm Adoption Strategies

The performance of an agent as well as the performance of the total system is hindered to a large extent if all the agents in the system strictly follow a single norm, i.e., either to cooperate or to defect throughout the lifetime of simulation, this is problematic. Let's examine a game theoretic view of the decision-making strategy about whether to cooperate or to defect. If an agent defects a traffic rule there is a possible accident, leading to a low performance of the agent and the system. If instead, all agents in the system cooperate they have to wait for each traffic signal even though there may not be a possible collision, thus leading to a decrease in the performance in the system as well. Accidents when occurred have two main consequences. There is penalty for the group as well as there is penalty for the individual. Thus, instead of rigidly following a norm, revising norm dynamically would yield possibly superior results. Five norm adoption strategies are considered for experiments. The two adaptive strategies under consideration were proposed earlier by Lacey and Hexmoor (Lacey and Hexmoor, 2003). The norm adoption strategies are listed here:

1. Unilateral Cooperation
2. Unilateral Defection
3. Adaptive Cooperation
4. Adaptive Defection
5. Cooperation based on agent rank

Unilateral Cooperation: In this strategy all the agents in the system cooperate to follow the traffic signals. That is all the agents must stop for traffic signals. In this strategy there will be no accidents since all agents cooperate.

Unilateral Defection: In this strategy all the agents in the system defect on traffic signals. In this strategy there will be a number of accidents.

Adaptive Cooperation: In this strategy, agents whose performance is higher than the performance of the system cooperate and the agents whose performance is lower than the performance of the system defect. In this strategy since agents whose average is lower than system average can defect, they can increase their performance over time. Here we predict that there will be less deviation in the performance of the agents

Adaptive Defection: In this strategy, agents whose performance is higher than the performance of the system defect and the agents whose performance is lower than that of the system cooperate. Here since agents that are performing better continue to defect, we predict that there will be more deviation in the performance of the agents.

Cooperation based on rank: In all the previous strategies agent communication is not considered in the norm revising factors. If instead agents are given more information (beliefs) about other agents position and the strategies they adopt. From this the agent knows prior that if there is a possible accident. In this situation one of the two agents cooperates while the other defects. The agent that cooperates is decided by the rank of the agent. Rank of an agent at any time is computed as the number of trips made by the agent. Here we assume that higher rank agent chooses to cooperate. This can be visualized as acquiring a resource by an agent in a grid-based network. Instead of both trying to proceed and leading to a collision, one of the agents cooperating will lead to better payoffs for both the agents in the long run. This may lead to no accidents but instead there may be a little delay to complete the total assigned trips.

A Model for Efficacy of a Norm

To study the efficacy of norm adoption strategies, we consider that agents as socially aware and show intelligent behavior. It is not necessary that all agents follow the same strategy in the system. Considering agents as autonomous and free to choose from the existing Norm-driven strategies, a question that arises is “which strategy should an autonomous agent adopt?” Considering a group of agents that adopt heterogeneous strategies upon entering the systems, what norm is the most beneficial one to adopt? To answer this question we adopt a model based on Bicchieri’s work on norms of cooperation (Bicchieri, 1990). In this model, agents are considered to be selfish, which means that they always try to increase their individual utility and ignoring social utility.

- Consider for simplicity that there are only two competing strategies from the previous section i.e., Unilateral Defection (D) and Conditional Cooperation (T). Conditional cooperation can be seen as tit-for-tat strategy i.e., an agent only cooperates if the opponent cooperates.
- Frequency of adhering to a strategy *I* at time t is denoted by $\boldsymbol{P_t}$. This is computed as the proportion of population (of agents) following strategy *I* at time t. since we are considering two strategies in this model, the frequency of other strategy is $\boldsymbol{1-P_t}$.

$$\boldsymbol{P_t} = n\,(I)\,/\,N$$

$n\,(I)$- represents number of agents following strategy I

N – represents total number of agents in the system.

- A Strategy is considered to be *efficient* or *stable* if the number of agents following it at time *t+1* is either greater than or equal to the number of agents following it at *t.*

  i.e., when $\boldsymbol{P_{t+1}} \geq \boldsymbol{P_t}$.

  This definition is directly adapted from Bicchieri's work (Bicchieri, 1990). She presented this as her main claim.

- We define an *inflexion point* denoted by $\boldsymbol{P^{\wedge}}$**,** as the threshold frequency that determines whether strategy *I* is *efficient* i.e., the strategy would upheld by at least as many agents that are currently adopting it. This is illustrated in the Figure 7.

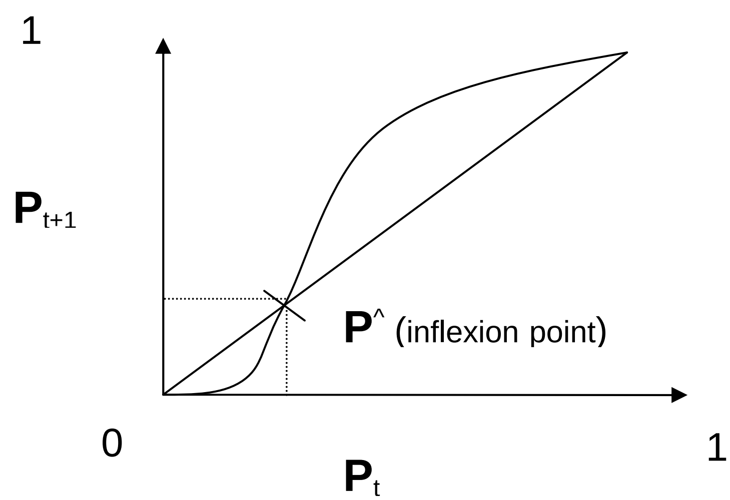

Figure 7. Inflexion point

- Δ_{DD} represents the payoff at time *t* of agent for adopting strategy D if the opponent adopts strategy D.

  The same definition holds for Δ_{TT}, Δ_{DT}, Δ_{TD}.

- The *inflexion point* based on Bicchieri (Bicchieri pp859, 1990), $\boldsymbol{P}^{\wedge}$ is computed by the following formula.

$$\boxed{\boldsymbol{P}^{\wedge} = (\Delta_{DD} - \Delta_{TD}) / (\Delta_{TT} + \Delta_{DD} - \Delta_{DT} - \Delta_{TD})} \quad \text{(equation 1)}$$

- For our simulation, the payoff table (table 4) is computed based on number of accidents, denoted by A_c, number of agents denoted by N.

Opponent Agent

Agent		Cooperate	Defect
	Cooperate	$2\ A_c\ /N$	0
	Defect	A_c	$A_c\ /N$

Table 4. Pay off Matrix

The payoff matrix is considered symmetric and the payoffs in the table 4 represent payoffs for the row agent. For example, If both agents Cooperate they each receive a payoff of 2^*A_c /N. On the other hand, if one cooperates and the opponent defects the cooperator receives a zero payoff and the defector receive a payoff amount of A_c. If both agents defect, they each receive a payoff amount of A_c /N.

Using the payoff matrix in table 4, the total payoffs for n iterations are recomputed as:

$\Delta_{TT} = 2nA_c\ /N$ $\qquad\qquad$ $\Delta_{TD} = n\text{-}1$

$\Delta_{DD} = nA_c\ /N$ $\qquad\qquad$ $\Delta_{DT} = A_c + (n\text{-}1)\ A_c\ /N$

As defined earlier Δ_{TT} is the payoff that a conditional cooperator achieves when she is confronted by another conditional cooperator. The payoff obtained in a single iteration is $2A_c /N$, since both choose to cooperate. The payoff illustrated here is the payoff that conditional cooperator achieves against another conditional cooperator in n-iterations of the game. Similar explanation holds for other three payoffs for n-iterations.

Solving for threshold frequency from the equation defined in equation 1, we have the inflexion point.

$$\boxed{\mathbf{P}^{\wedge} = 1/ (n-N+2)} \quad \text{(equation 2)}$$

IV. Experiments and Observations

Simulations are run on our simulated city to quantify the performance of norm adoption strategies discussed earlier. The parameter set assumed for the experiments performed is illustrated in table 5. A population size of thirty is assumed for the city traffic grid scenario. A total of 200 trips are carried out for each strategy.

Parameter	**Value**
Number of agents	30
Number of Trips	200
Individual Penalty	25
Group Penalty	10
Signal wait period %<NS, EW>	50,50
Simulation Panel Refreshing rate	30 system cycles

Table 5. Summary of Experimental Parametric values

Signal wait period for each direction is 90 time cycles. This is the same *wait time* for both East-West and North-South directions. If an agent is involved in an accident the penalty for the accident is 25 time cycles. The penalty is given to the agent that disobeyed the traffic signal while the other agent involved in the accident does not receive any penalty. The agent has to be idle during the period of the penalty. There is also a group penalty of 10 time cycles. During this time the junction is blocked for the through traffic where the accident has occurred. The results are shown in table 6 in terms of the time taken for each strategy to complete the assigned number of trips and the number of accidents involved in each strategy. We concluded that dynamic norm revision yielded superior results, compared to unilateral cooperation and defection. The unilateral cooperative strategy took 2559 number of cycles to complete the trips assigned and there were no accidents. This is due to the fact that all the agents are following the cooperative norm, i.e. they have to wait for the specified amount of time at the junctions even though there may not be a possible collision. While the unilateral defection is also inferior because of the number of accidents involved. In this strategy, although the journey completion is faster, there are a large number of accidents. Table 6 records that it took 2424 cycles to complete the required number of journeys and the number accidents involved is 106, which is considerably a large number of accidents. This is particularly not desirable in time critical tasks. The adaptive strategies on the other hand showed a substantial improvement. Keeping the number of accidents low these strategies achieved better results. Adaptive cooperation and defection resulted in 48 and 41 accidents respectively.

Norm Strategy	**Collisions**	**Time**	σ
1.Unilateral Cooperation	0	2559	0.75
2.Unilateral Defection	106	2424	0.97
3.Adaptive Cooperation	48	2191	0.64
4.Adaptive Defection	41	2045	2.50
5.Rank based cooperation	0	1668	0.61

Table 6. Summary of results

The last column in the table 6 shows the standard deviation of the number of trips completed by each agent in the system. Standard deviation in the first three strategies is considerably low. On the other hand, the standard deviation for adaptive defection strategy is 2.50. This is relatively high since the agents that are performing better defected and resulted in large variation of performance of the agents. The last strategy is rank-based cooperation. This strategy is based on agent communication. Agents successfully prevent accidents based on cooperation by rank. The standard deviation in this case represents the deviation in the rank of agents. Since an agent with higher rank yield to an agent with lower rank, lower rank agents improve their rank over time. The deviation in this case is 0.61. This strategy resulted in the shortest time completion of trips. This shows that adding agent communication to norm strategy is beneficial to both agents and the system. The strategy that involved agent communication yielded the best results.

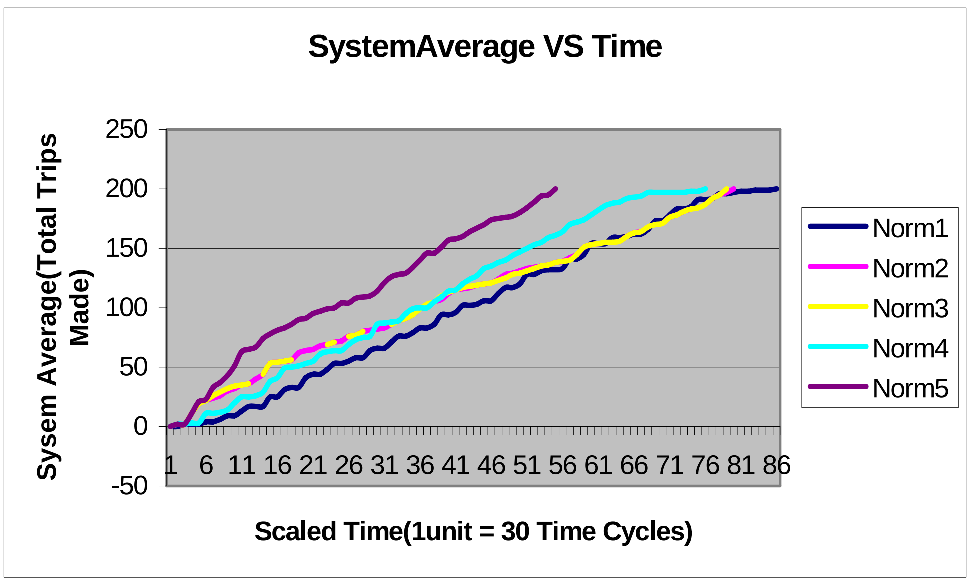

Figure 8. System Average trips versus time

Figure 8 depicts the system average versus the time. The horizontal axis represents the time scaled in 1:30 ratio i.e., one unit on the graph represents 30 time cycles in the actual simulation. As defined in the previous section system average is the total number of trips completed for each unit of time. All the five strategies show a steady growth in the system performance. The flatness of curve towards the end of norm 1 is due to the fact that a few agents are waiting at the junctions to complete the assigned task.

In another set of experiments we conducted by varying the population size that is cooperating in the system. This can be viewed as the probability that an agent cooperates or defects at a certain time slot. The results are illustrated in table 7 for a population size of 30 agents. The results show that as the number of cooperating agents decreases there are a higher number of accidents. The time taken is decreased, as the number of agents that are defecting is increased. The simulation that involved 20 cooperating agents yielded the best result. This simulation completed the task in much lesser time keeping the number of accidents low.

Number of Cooperating agents	**Collisions**	**Time**
25	35	2729
20	44	2464
15	70	2719
10	75	2309
5	86	2344

Table 7. Results for varying number of cooperating agents

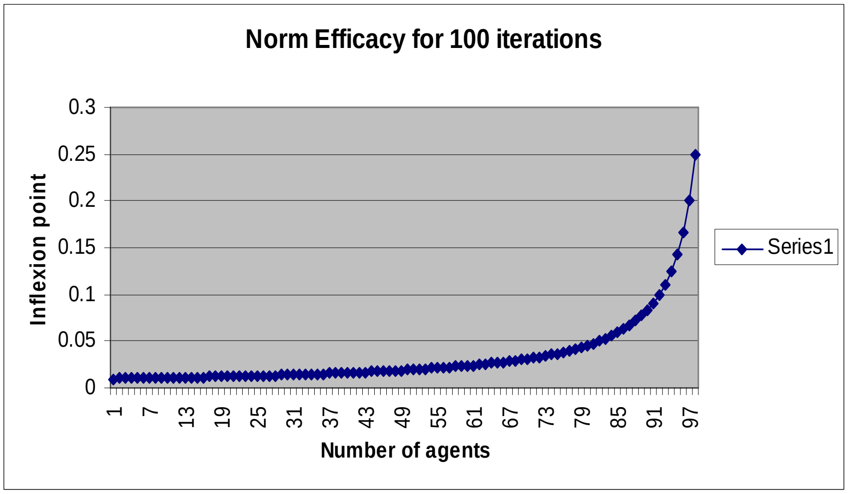

Figure 9. Inflexion point versus number of agents in 100 iterations.

Another observation is the efficacy of norm adoption strategies from equation 1. As discussed earlier the norm strategies we are considering are condition cooperation (T) and unilateral defection (D). In the payoff table (table 4) although we included the number of accidents, the *inflexion point* in the final formula only depends on the number of agents and the number of interactions that agents are involved in. Figure 9 is presented to show how *inflexion point* varies against the number of agents in the system. The norm efficacy is considered for fixed number of iterations, one hundred in this case. The figure indicates that in a fixed number of iterations, as there are a higher number of agents, the ratio of agents that should be cooperating is more. Otherwise the small portion of cooperating agents will be at loss after 100 iterations. As the figure shows that in a group of 100 agents there should at least as many as 25 agents that are cooperating (T) otherwise the population of defectors over a time can become dominant. This indicates that if a new agent enters the system at time t then it is beneficial for the agent to adopt cooperative strategy (T) when more than 25 agents in the system are adopting the same strategy. If not, other agents exploit the cooperative behavior of the agent entering the system. The steep raise of the curve towards the end is due to the fact that for large population sizes the cooperation can evolve and sustain only when there are relatively more interactions; i.e. iterations in our scenario.

Figure 10 shows the number of iterations versus *inflexion point*. This figure shows that as there are more interactions a smaller fraction of the agents need to follow the cooperative norm (T) to be *efficient* and *stable*. If there are a large number of interactions among agents then agents see it is beneficial to adopt the cooperative norm (T) rather than to defect. The curve starts at 1, indicating there should be a minimum number of iterations to study the *stability* of the norm. The number of iterations is starting from 49. The curve shows that the *inflexion point* decreases greatly at the beginning but then gradually stabilizes.

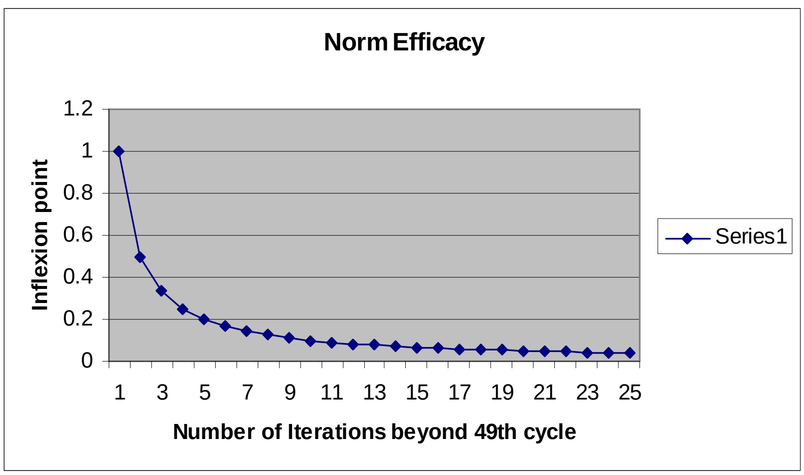

Figure 10. Inflexion point versus number Iterations

This suggests that in a group involving a large number of interactions, the group of agents following the conditional cooperation (T) strategy cannot be successfully dominated by isolated defectors entering the system. This is because agents involved in a large number of interactions come across the same agent many times. If an agent adopts unilateral defection that agent sees it would be at a loss in the long run because its defective strategy would be learned and punished by other agents in the group.

V. Conclusions and Future Work

The motivation for this work was to analyze the effects of norms, norm adoption strategies and efficacy of a norm adoption strategy in multiagent systems. Sets of experiments are performed to study effectiveness of the strategies in a simulated city traffic grid scenario. Our results indicate that in a multiagent system that is governed by norms; the norms regulate the cohesion among agent behaviors. The results also illustrate that norm-revising strategies are better than rigidly following a norm. As discussed in the previous section, the strategies of norm revision involving agent communication yield superior results since the agents attain cooperative equilibrium by mutual cooperation in successive interactions. The norm revising strategy involving agent communication is based on the game theoretic point of view. The results on the efficacy of norm strategy indicate that cooperation can evolve and sustain if there are a sufficient number of interactions among agents.

In the norm revision strategies we did not consider certain other important aspects of agents such as agent autonomy and trust among agents. When agent interaction takes place in multiagent scenario trust plays an important role to resolve the conflicts of cooperation. We also did not consider criticality of task assignment to an agent. Future experiments involving agent autonomy and trust are desirable as well as considering the heterogeneity of a population of different groups with different norm sets.

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