BEHAVIOUR ANALYSIS OF SOCIALLY MOTIVATED AGENTS

A DISSERTATION

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By

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Declaration

I declare that the work presented in this dissertation with title, “**Behaviour Analysis of Socially Motivated Agents**”, towards the fulfilment of the requirements for award of the degree of **Master of Technology** in **Computer Science & Engineering**, submitted to the **Department of Computer Science and Engineering**, **Indian Institute of Technology-Roorkee**, India, is an authentic record of my own work carried out during the period from **June 2015 to May 2016** under the guidance of **Dr. Rajdeep Niyogi**, Associate Professor, Department of Computer Science and Engineering, Indian Institute of Technology, Roorkee.

The matter presented in this dissertation has not been submitted by me for the award of any other degree of this or any other institute.

Date:

Place: Roorkee **(Tarun Garg)**

Certificate

This is to certify that the statement made by the candidate in the declaration is correct to the best of my knowledge and belief.

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ABSTRACT

Inclusion of multiple autonomous agents in the complex systems is highly increasing day to day. Multi Agent Sytems(MAS) are systems that involves a number of collabrative elements, known as agents. Agents are computing devices having two important functionalities – autonomous action i.e having the freedom to work independently and second, the capability of interacting with other agents in the system and with the society or environment.The Tragedy of the Commons (TOC) is a social dilemma where rational and self-interested agents utilizing a shared resource of fixed capacity leads to inefficient utilization of resource. In any society, two crucial aspects : individual and social concerns, are responsible to cause ineffective performance of system as well as individual. Since, these two aspect create a dilemmatic situation for an agent such as whether to contribute or exploit (enjoy own profit without caring about the society). Hence, the proper balancing between individual and social concerns is needed to avoid dilemma. In order to solve this problem, we propose a decentralized approach based on the Altruistic behavior of agents, known as *Altruistic Decision Making Approach* (ADA).

In ADA, agents communicate with each other and adjust their load in accordance with current context, i.e., the agents are able to dynamically vary their load to balance the individual and social considerations and also work in resource bounded fashion. To judge the efficacy of the ADA, it is compared with another state of-the-art decentralized approach on different social conditions and is found better than its competitor. Thus, it is observed that the ADA is simple, efficient and powerful decentralized approach to solve the TOC problem.

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Dedication

To my parents, for giving me the best education they could

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CHAPTER 1

INTRODUCTION

Multi Agent System(MAS) is collection of elements or components that are assembled to achieve a common goal. These elements are known as agents and simulate the owner in the real world scenario. Agents are computer systems works independently in place of its owner. The vitality of an individual in a social environment depends on the behaviour of the members of the society. Some fascinating computational problems in the societies of the agent include inconsistency that involve the reduction of the system throughput when more consumers are added to an existing shared resource. A local utility-maximizing decision-making policy by a member causes a loss of utility to all members which further aggravated by arising other social dilemmas. These types of problematic scenarios occurs very often in natural and social science societies. These situation can be viewed as complex system in MASs.

Usually, the term *Complex* delineate a system that is very difficult to understand and validate by design or function or both. Thus, to predict the behaviour of such a system, a comprehensible representation of its is needed which can be termed as *model of the system*. However, there is no concise definition of the complex system. *To us, the complexity means the structure of the society and the various characteristics of the individuals involved in the society*.

The survival of an individual in a society relies intensively on the behaviour of the populace. Some fascinating computational problems in the societies of the agents include antilogies' that the addition of more resources in an existing system deteriorates the performance (throughput) of the system. Furthermore, the parochial viewpoint of a social agent to maximize its own profit results in inefficient utilization of common resource and insidiously ruins the utility for everyone in the society. Such local decision-making by an agent leads to problematic scenarios which can often appear in natural and artificial societies.

In a society, a public good is shared amidst all the members and has fixed capacity. If an individual strive to overload the resource, the perceived utility to others, reduces sharply and ultimately the entire society get doomed. One of the excellent example of common resource shared by many people is public roads. Every individual keeps his/her own interest in mind - typically how to get to work with ease and quicker. But when everyone plans to go by road in order to meet traveling needs, the roads jam up and the congestion problem arises. Generally, in a distributed scenario, the resource of interest is accessible to all the members. When every individual tries to gain the highest mileage from given resource and disregards the well-being of the society. As the demand for the resource goes beyond the availability, every individual who puts an additional unit of load directly affects the others who can no longer reap the benefits. This situation originate a well recognized social dilemma known as the Tragedy of the Commons (TOC).

In early nineties, Turner [1] has drawn the attention of researchers towards the tragedy of the commons in the context of autonomous agent systems. In this work, some interesting characteristics of the agents and resource are discerned that predispose to TOC. Though, the socially intelligent agents are able to solve problem autonomously by interacting with similar agents, but their economic viewpoint and the negligence of society-welfare in the pursuit of personal advantage can lead to unexpected results and inefficient utilization of the resource. Notwithstanding the fact that it is a thorny problem, with no clear, efficacious solutions, there exists a good volume of works (a survey of which is provided in Chapter 3), seeking to achieve the solution for the problem.

In addition to balance individual and social considerations, it is desired that intelligent agents work in a resource bounded manner. There is no unlimited time and resource, thereby agents must be able to amend their load according to current context. In this report, we address these issues and propose a novel decentralized approach based on the altruistic behavior of the agents, hereinafter, referred to as *Altruistic Decision Making Approach* (ADA), to solve the Tragedy of the Commons problems. It uses a social motivation of an agent (i.e., how much an agent is interested to contribute for the society) to simultaneously maintain individual and social considerations. The load for an agent is determined on the basis of its social motivation factor to deal with dynamically varying society conditions and to utilize resource efficiently.

Further, to investigate its relative performance, it is compared against another state-of-the-art decentralized technique. And experimental results reveal that the ADA performs better to its competitor on the four different scenarios. The obtained results show that the ADA is a simple, light, and a technique to solve the Tragedy of the Commons problems.

The rest of the report is organized as follows. Chapter 2 details the Tragedy of the Commons problem. Chapter 3 outlines the survey of previous research work to solve the Tragedy of the Commons problem. Chapter 4 introduce the proposed methodology. Experimental settings and the simulation results are described in Chapter 5. Finally, Chapter 6 concludes and presents a future scope of the work.

CHAPTER 2

PROBLEM STATEMENT

In 1833, William Forster Lloyd [2] presented the tragedy of the commons scenario as a rebuttal to "invisible hand" theory of Adam Smith [3]. Lloyd investigated the depletion of a common pasture shared among rational, utility-maximizing herdsmen. In order to formulate the problem, Llyod assumed a common pasture with capacity C (i.e., pasture can support at most C cattle) and the system of commons will sustain as long as the number of cattle N is not exceeding the capacity (i.e., $N < C$). When $N < C$, adding a cattle benefits the herdsman, without alleviating others benefit. On the contrary, when $N > C$, addition of any single head reduces the grazing quality for all. Later in 1968, Garrett Hardin [4] observed that Lloyd 's work is not limited to population control, but also has extensive implication for gradually and insidiously exploitation of any common resource. According to Hardin's parable the tragedy of the commons is as follows: *"Therein is the tragedy. Each man is locked into a system that compels him to increase his herd without limit - in a world that is limited. Ruin is the destination toward which all men rush, each pursuing his own interest in a society that believes in the freedom of the commons." [4]*

In this thesis, we will try to formulate a model which will depict the rational behaviour of an agent based on its greed and social factor. Social factor describes the social welfare ness of an agent in Mutli Agent Systems(MASs). Later we plot graph and makes an experimental study on the behaviour of agents.

2.1 Real world scenario of TOC

As a self-interested nature, each agent or herdsmen will have the motivation of maximizing his individual profit. So based on this motivation of increasing his gain each herdsman has a question in his mind, “ what is the utility to me by increment an animal on his flock??”. This utility has two important impact . First , the increment of an animal will result in direct increment of utility for the herdsmen and this utility can be considered as positive component as it will provide direct benefit to the herdsmen on the sale of the animal. Second, addition of an animal will affect the whole society and may leads to overgrazing of the resource and is a negative component. However , overgrazing effect is shared by all the herdsmen so the negative component effect is in fraction for the decision making herdsman. Adding the effects of both components , the herdsman will decide to increase another animal to gain the maximum utility and on the other side, all herdsman concludes the same and will also decide to increase on the shared common resource. This leads to the exploitation of the limited resource ad so in this manner each agent is get interlocked into the system that forces them to increment their profit without a limit and leads to problem Tragedy of Commons.

Figure 1. Multi Agents on shared resource.

Nowadays , In wordly affairs the impact of TOC currently is more than it was never before as we can see its effect in ozone depletion, overfishing and extinction of species, and destruction of the rain forests. TOC does not have impact only in human affairs but it’s has relevance to in computer science. Some examples in computer science that have shared resource and which is endangered are memory, power, disk space communication channel bandwidth and physical space and materials. Network packet transfer is another example in Computer science which exhibit behavior similar to that of Tragedy of Commons problem.

Network packet transfer may have tragedy when a host in the system does not follow the protocols and dominate the overall shared resource and its utilization by using self-centered strategy. Most of the communication systems such as ALOHA protocol , Ethernet system and the TCP/IP networking uses a common resources which is shared among the users of the system. In TCP/IP the network packets from the different users share the same links and the buffer capabilities of the routers.

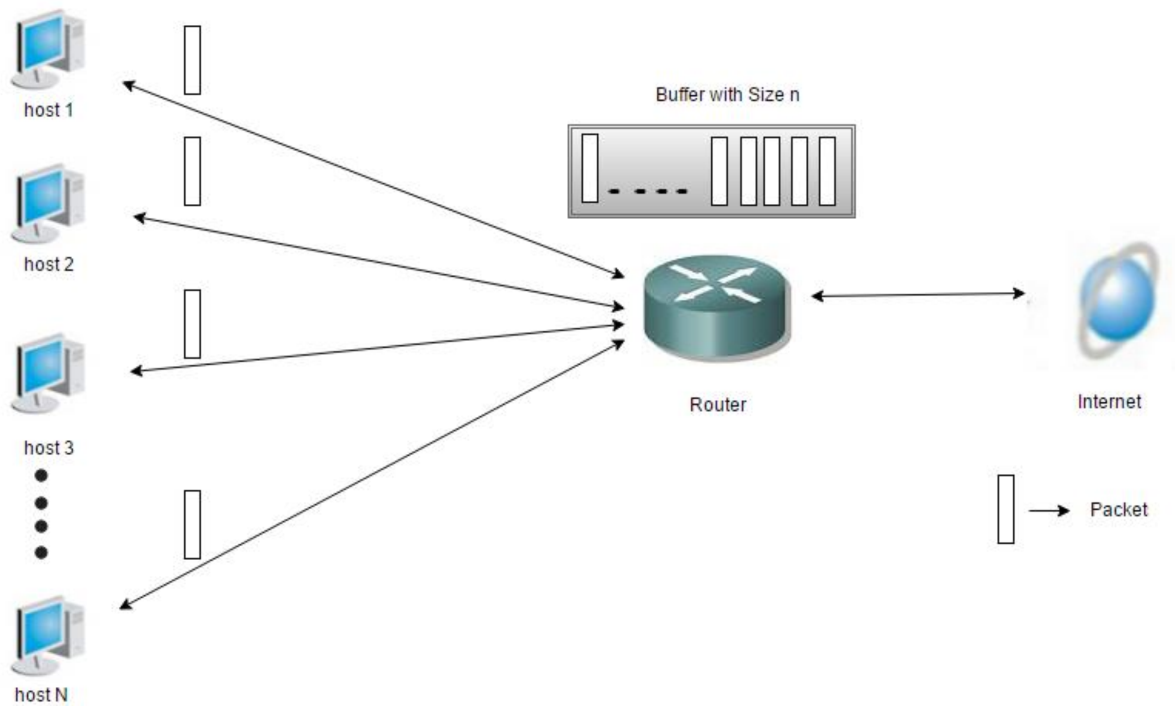

Figure 2. N hosts accessing a common communication link .

Here router works as a common shared resource similar to the pasture in the herdsmen problem. As, the user of the system which is self- interested in nature will try to maximize it’s usage on the router by transferring more no. of packets leads to uneven delay and drop of the packets during transfer due to fixed size buffer at the router and creates un-stability or congestion in the system as depicted in Fig 2.The main reason behind the un-stability is that networks and protocols usually anticipate no guarantees that the users will respect the rules or whether they will cheat.

2.2 Issues in modelling the TOC

The TOC situation is a complex system which is consist of multiple agents and their environments. This can be viewed as multi-agent system. Further, the agents are also divided into different categories depending upon their behavior.

Some of the categories are as:

- **Passive agent:**- an agent without any goal
- **Active agent:**- an agent with a simple goal

Moreover, these agents have several characteristics as:

- **Autonomy:**- The agents have self-awareness and autonomous behavior
- **Local views:**- The agents do not have full knowledge of the system (i.e., lack of global knowledge)
- **Decentralization:**- In the society of agents there is no specific controlling agent.

All these different features of agents made the problem complex to understand and predict the group behavior.

2.3 Game theoretic aspect of TOC

It relates to a sort of game interaction between competing agents related to the utilization of a common resource which is often is subject to over exploitation and leading to eventual depletion. Now, try to model this game and try to understand the behavior of these agents. Suppose, two timber agencies are involved logging trees. Each agency can use effort e_i. Note that, the number of trees logged is proportional to the effort put in by agencies.

- e_1 : effort put in by agency 1.
- e_2 : effort put in by agency 2.

The payoff corresponding these two efforts can be defined as :
Payoff for agency 1

$$U_1(e_1, e_2) = e_1 \times (100 - (e_1 + e_2)) \qquad (1)$$

Payoff for agency 2

$$U_2(e_1, e_2) = e_2 \times \big(100 - (e_1 + e_2)\big) \qquad (2)$$

Where $0 \le e_1, e_2 \le 100$ and $e_1 + e_2 \le 100$

Note that, payoff also decreases with total effort as both of them put together more effort , the more trees are cut and less left for future.

$$U_1(e_1, e_2) = e_1 \times (100 - e_1 - e_2)$$

$$= 100e_1 - e_1^2 - e_1 e_2$$

Now, to find best response e_1 for a given effort e_2 , i.e., maximize payoff

$$\frac{d\,U_1}{d\,e_1} = \frac{d}{d\,e_1}\,(100e_1 - e_1^2 - e_1 e_2)$$

$$\frac{d\,U_1}{d\,e_1} = 100 - 2e_1 - e_2 = 0$$

$$e_1^* = \frac{100 - e_2}{2} \qquad (3)$$

Similarly , for e_2

$$e_2^* = \frac{100 - e_1}{2} \qquad (4)$$

Each is playing his best response, i.e., the Nash equilibrium where best responses intersect.

By solving (3) and (4) ,

$$e_1^* = \frac{100}{3}$$

$$e_2^* = \frac{100}{3}$$

The outcome at Nash equilibrium ,

$$(e_1^*, e_2^*) = (\frac{100}{3}, \frac{100}{3})$$

Payoff to each agent at Nash equilibrium

For agency 1,

$$U_1\ (e_1^*, e_2^*) = U_1(\frac{100}{3}, \frac{100}{3})$$

$$U_1\ (e_1^*, e_2^*) = \frac{10000}{9}$$

For agency 2,

$$U_2\ (e_1^*, e_2^*) = \frac{10000}{9}$$

Now, apply an alternative approach to yield a higher payoff to each agency

Let both the agencies collaborate to maximize the payoff:

Joint payoff :

$$= U_1(e_1, e_2) + U_2(e_1, e_2)$$

Net Payoff :

$$= U_1(e_1, e_2) + U_2(e_1, e_2)$$

$$= e_1 \times (100 - (e_1 + e_2)) + e_2 \times (100 - (e_1 + e_2))$$

$$= (e_1 + e_2)\left(100 - (e_1 + e_2)\right)$$

$$U_t(e_t) = (e_t)(100 - e_t) \qquad (5)$$

To maximize net payoff,

$$\frac{dU_t(e_t)}{de_t} = 0$$

$$e_t^* = \frac{100}{2}$$

Let $e_1 = e_{2\,,}$

$$e_1^* = e_2^* = \frac{100}{4}$$

Payoff to each agent at Nash equilibrium

For agency 1,

$$U_1\,(e_1^*, e_2^*) = \frac{10000}{8}$$

For agency 2,

$$U_1\,(e_1^*, e_2^*) = \frac{10000}{8}$$

Net payoff in case of joint effort is greater than Nash equilibrium payoff. At Nash equilibrium, both uses more effort than required which is leading faster depletion of common resource and lower utility to all stake holders. Hence, *the solution is to impose regulatory framework that curve over utilization.*

CHAPTER 3

RELATED WORK

In early nineties, Turner [1] has drawn the attention of researchers towards the tragedy of the commons in the context of autonomous agent systems. In this work, some interesting characteristics of the agents and resource are discerned that predispose to TOC. Though, the socially intelligent agents are able to solve problem autonomously by interacting with similar agents, but their economic viewpoint and the negligence of society-welfare in the pursuit of personal advantage can lead to unexpected results and inefficient utilization of the resource. Notwithstanding the fact that it is a thorny problem, with no clear, efficacious solutions, there exists a good volume of seeking to achieve the solution for the problem.

In 1968, Hardin [4] describes TOC with respect to a pasture land shared among multiple herdsman. Herdsman have the ability to increase as much no. of cattle on the pasture to maximize their profit without even considering the benefit of the society and so lead to the tragedy. Hardin's proposed methodology simulates many real word scenarios like phishing , pollution management and road traffic control etc.

Enormous researchers has depicted TOC in various scenarios such as computer network , Distributed artificial Intelligence (DAI) , economics and also with respect to game theoretic perspective. In 2012, Diekart [12] published an article titled "The Tragedy of the Commons from a Game-Theoretic Perspective", in which he explained a famous "Prisoner's Dilemma" problem in relation with TOC. According to Prisoner's Dilemma , there are two players who has to take a decision from the two options available and the decision of one is vitally depends on the decision made by the other one , and is also described as two thieves arrested by police making decision independently whether to confess or deny to a crime. The game is based on individual cooperation of each thieves and so the police told each of them – if one confess and other deny the thief who confessed will get less term of prison in comparison to the other one , if both confesses both will be punished and if none of them confesses then police will do nothing and this will generates four different scenarios as shown in Table 1. between the prisoners to collaborate and only 1 state is a nash equilibrium in which both of them confesses. Nash equilibrium is a situation in which neither of the party gets profit by interchanging its decision while other party have does not deviate from its strategy.

Table 1. Prisoner's Dilemma

	Confess	**Deny**
Confess	**3 , 3**	**1 , 10**
Deny	**10 , 1**	**2 , 2**

Now the issue is , that both the prisoners can deny and get the optimal solution but that state is unstable state due to lack of trust in between . For example, if they are in state 4 , and prisoner 1 get to know that prisoner 2 will always deny so he can change his decision to confess and improves his sentence from 2 to 1 , similarly the prisoner 2 can think so the only Nash equilibrium in this game is that both the prisoners confesses to the police so that they will not get any benefits from deviating from his decision.

Comparison in between this and Hardin's Tragedy of the Commons is made by Diekart. He formulated the problem by stating that the no. of choices a person involved in the society is equivalent to that of in the Prisoner's Dilemma. i.e, the payoff received by every co-operative agent by addition of a cattle is 1". He also stated that if any one of the agent does not cooperate and puts a second cattle in the society(pasture) , then he will receive a payoff of $2 - \alpha$ and others will receive the payoff $1- \alpha$ and will have the same scenario as Prisoner's Dilemma as shown in Table. 2. The

Table represents that if both the agents in the society are non-cooperating will leader to the payoff 0,0 which is not a nash equilibrium . So this shows that , if all agents are defecting is not profitable for them and will never be nash equilibrium in opposition to Prisoner's Dilemma.

	Cooperate	**Defect**
Cooperate	**1 , 1**	**1- α, 2 - α**
Defect	**2 - α, 1- α**	**0 , 0**

Table. 2 Tragedy of Commons Using Prisoner's Dilemma

But still the proper balancing between individual and social concerns is needed to avoid dilemma.

Later , multiagent systems researchers have particularly raised issues about the task-sharing policies [5] and suggested a distributed problem solving methodology. In their approach a single agent behave like planner who makes all resource allocation decisions. Durfee *et al.* [6] proposed a new framework that uses partial global plans in order to foster different style of cooperation between distributed problem solvers. Turner [1] found that the tragedy of commons scenario may arise in distributed artificial intelligence (DAI) when agents share a resource. And he suggested some theoretical guidelines to avoid the Tragedy of the Commons problem. There are many DAI's system where the agents share a common resource. The most evident scenarios of such *Common pool resource* . Table 3 describes the properties for some common resources for distributed artificial agent systems.

The techniques to avoid the Tragedy of commons are as follow

• **Multiagent Planning Approaches:-** these approaches are suggested by Cammarata et.al. [**5**] and one agent work as planner and all decisions for resource allocation to other agents are taken by this agent. The major drawback in these approaches as to take these decisions planner requires nearly perfect knowledge of the other agents, society and about the share resources.

	Traditional	Processor	Communication Channel	Power	Sensor	Sonar
Resource	grass	cycles	bandwidth on shared channel	power from renewable resource	access to sensor	quiet environment
Consumers	cattle	processes	conversations (messages)	agents	agents	agents' sonar
Action	grazing	computation	sending messages	recharging	access	sonar pulses
Owners	herdsmen	DAI agents	DAI agents	DAI agents	DAI agents	DAI agents
Gain	head of cattle	increased throughput	inc. message throughput	inc. ability to work	accuracy, decreased uncertainty	accuracy, decreased uncertainty
Cost	decreased quality per head, degraded pasture	dec. speed/process	noise, collisions, dec. speed of delivery	dec. power to others	dec. access for others, overhead for sensor	noise⇒sonar interference
Result	collapse of pasture (poss. irrecoverable)	thrashing, unacceptable throughput	contention	contention for power, some may be out of power	"starvation" for sensor data, sensor processing or message overload	inability to use sonar

Table 3 . Shared Resource For DAI [1].

• **Monopolies:-** [?] in this approach an agent own the resource and decide the utilization of that resource by other agents. The Drawback with this approach is similar to planning approach. The owner will not take care of the goal of other agents and it self can exploit the source.
• **Privatization:-** this is another way to avoid the TOC by assigning ownership of the shared resource. The major danger of it are (i) the privateer may itself exploit the resource and (ii) not ensures that all agents get their fair stake.

• **Mutual coercion and mutually agreed upon:-** to make cooperation between all the agents to exploit the resource. The lacuna in this method is similar to multi agent planning as it need a central controller to control all the activity and responsible for mutual agreement between agents. After knowing the wide-spread implications of the TOC problem, over the past few years researchers have been investigating the ways of averting this problem. Tumer *et al.* [7] introduced *the theory of Collective Intelligence (COIN)* based approach to tackle social dilemmas in multiagent system. however, this approach needs an *omniscient* agent to choose a utility function to be optimized. In this context, Mundhe *et al.* [8] proposed a genetic algorithm (GA) based adaptive framework, and investigated the its applicability for developing co-adapted agent societies.

Saha *et al.* [9] proposed an algorithm to achieve optimal resource utilization of a public good in the society. Their algorithm is based on local decision procedure where each agent has local information in terms of perceived utility.

Algorithm : Step by Step description of local decision procedure[9].

***Step1*:** each agent put a random load l_i^0 on the common resource and it is assumed that $\sum_i l_i^0 < C$.

***Step2*:** each agent *i* increases its load l_i(by 1 unit)

***Step3*:** agent *i* computes its utility. If received per unit utility is greater then the best per unit utility it recieved in the past , GOTO step2.

***Step4*:** agent *i* decreases its load and set up_i to *false* and p_i = 1;

***Step5*:** agent *i* decreases its load with the probability p_i, only if up_i is *false.*

***Step6*:** if agent *i* had increased its load in step 5 and received per unit utility lower than ever received the best per unit utility, it decrements its load and do half the p_i , otherwise set up_i to *true.*

Step7: if p_i is *true and* $p_i > p_{Threshold}$, GOTO step 5.

***Step8*:** agent *i* maintains it's current load l_i.

In [10],a distributed computational scheme is developed to avoid the TOC problem, where each agent is associated with an aspiration level. Individual 's aspiration level is decided on the basis of utilities. The load applied by an individual on the resource is adjusted in accordance with the value of its aspiration level. An aspiration level corresponds the level of satisfaction provided to the individual which is managed according to the past experience. Thereby, in this method, each individual put the load on the resource in accordance with its aspiration level to maintain the sustainability and the performance of the system.

Formulation of the Problem :

a: denotes an agent

N : total number of agents and n=| N |

$U_a(t)$: utility of the agent a at time t

$H_a(t)$: aspiration lvel at time t

$L_a(t)$: the load

T_L: $\sum_{a=1}^{N} L_a(t)$ total load of the system

µ: threshold load

Agent a's utility is computed by the function

$$U_a(t) = \begin{cases} L_a(t)\,, & T_L < 0 \\ L_a(t) * \alpha e^{-k(T_L - \mu)}\,, & T_L \geq 0 \end{cases}$$

where k is the environmental factor and α is a constant.

Maintaining the aspiration levels and loads

The load applied by an individual is depend on its aspiration level which is balanced in accordance with the utility received from its load. In this technique, two schemes are described to maintain the aspiration levels as well as the system load. Further, these schemes are referred as the category of the agents as (i) Eager agent and (ii) Prudent agent.

Eager agents: these agent adjust their aspiration as follows:

If $U(t) > h(t)$ **then**

$h(t + 1) = \beta U(t) + (1 - \beta)U(t - 1)$

$\gamma = t$

$L(\gamma) = L(t)$

$L(t + 1) = L(t) + \alpha$

If $U(t) < h(t)$ **then**

$$h(t + 1) = h(t)$$

$$L(t + 1) = \frac{L(\gamma) + L(t)}{2}$$

where $\beta \in (0,1]$ is the learning rate. γ is the last time when the aspiration level of agent increased.

Prudent agents: these agent adjust their aspiration as follows:

If $U(t) > h(t)$ **then**

$$h(t + 1) = \beta U(t) + (1 - \beta)U(t - 1)$$

$$L(t + 1) = L(t) + \alpha\,(t)$$

If $U(t) < h(t)$ **then**

$$L(t + 1) = L(t - 1)$$

$$h(t + 1) = h(t)$$

In this way, both type of the agents adopt their aspiration levels and avoid the over exploitation of the shared resource.

Akarsh *et al.* [11] made a comprehensive experimental study in order to analyze the tragedy of common scenario in the context of multiagent systems. They suggested three types of algorithms corresponding to the different behaviors of the agents. Firstly, they assumed that the agents are self-interested and focus on maximizing their own profit only. In this case, the survival time of the society is very less. Secondly, the agents consider the well-being of society to some extent. In this case, the survival time of the society is more in comparison to previous approach. In the last, it is assumed that the agents are socially motivated and they are also willing to sacrifice for the welfare of the society. Hence, this approach yields much better performance as compared to both the previous cases.

CHAPTER 4

PROPOSED METHODOLOGY

In this section we are going to present the proposed method. First we have shown the motivation for our work and some of the drawback in existing algorithm . Afterwards, we had give a simplistic model to describe the Tragedy of Commons for easier understanding of the problem.

4.1 A few drawbacks in existing solution

In this section we present the drawbacks in some of the existing proposed work on the Tragedy of the Commons. Most of the researchers have already made attempts to balance two contradictory aspects of decision making in any multiagent society: individual gain and social concern. The first one means the temptation for an agent to free ride on the efforts of others, since there is no restriction for the utilization of the public good. Whereas, the seconds denotes the survival time of the society. Although, in [9], a decentralized algorithm is introduced which typically depends on the minimal local information. The algorithm is able to avoid over exploitation of resource, since each agent tries to optimize resource utilization. But the major drawback of this approach is that the issue of survival time of the society is not taken care.

In addition, [11] pointed out that if the agents are not interested in free-ride only, but have some degree of sacrifice, the survival time of the society can be improved. However, this approach is a centralized approach and not effective in dynamically changing distributed environment where to obtain global of the system is not possible.

4.2 Motivation for Proposed Solution

A proper tradeoff between individual and social concerns is required for the efficient and effective operation of a decentralized algorithm. In the present context, some algorithms are decentralized but not focus on the survival time while others consider the survival time but highly centralized. In this context, the authors propose a decentralized technique which is able to optimize both the objective of the TOC: individual gain and social concern, simultaneously.

4.3 Altruistic Decision-making Approach

4.3.1 Modeling the Tragedy of the commons:

The theoretical model for the Tragedy of the Commons problem, to be used, as follows: It is assumed that the society is composed of resource and a finite number of agents (herdsman). The resource has a fixed capacity *C*, i.e., it can effectively support *C* units of load, but if the total loads *L* applied by all the agents is more than resource capacity, the perceived utility (throughput) for all the agents decreases. The mathematical model for the above mentioned constraint is given as:

$$U(L) = \begin{cases} \lambda, & if\ L \leq C \\ \lambda * \dfrac{C}{L}, & if\ L > C \end{cases}$$

Where *U*(*L*) represents the per unit utility when the total load applied on the system is *L* and λ is a constant. Here, it is evident by (1) that when the applied load is less than resource capacity, it is pure gain for an agent. And by knowing this, any rational agent conjectures that adding more load is a better alternative for maximizing the profit. In spite of that, it is also evident that when every agent will make the selfish choice, the per unit utility decreases and everybody suffers. In such circumstance, the social synergy of the agents come in rescue of whole society by reaching a co-operative equilibrium to utilize the resource optimally. We made an attempt to avoid such an undesirable situation by utilizing the altruistic behavior of the agents.

4.3.2 Algorithm

We provide a decentralized algorithm to resolve the Tragedy of the Commons problem. Further, some assumptions are made as

(i) The resource has fixed capacity and non-renewable, and
(ii) The resource is freely available to all the agents.

Further, it is considered that each agent has two levels of requirements:

(a) ***minimal requirement** (r_i^{min})* - corresponds to minimum need that necessary to survive in the society, and

(b) ***eagerness** (e_i)* - represents the additional requirement.

And each agent is associated with a ***motivational factor*** m_i which denotes the extent of Altruism for agent.

Initial Conditions.

In order to design *An Altruistic Decision Making Approach* (ADA) to resolve the TOC, the terminologies and initial conditions are given as:

• *A[i]*, *i* = 1,2, ...*N* are the agents in the society
• Φ : Shared Priority Queue to maintain the m_i of all agents in reverse sorted order
• *C* : capacity of the shared resource
• r_i^{min} *:* minimal requirement of an agent *i* and is selected from interval $[1, \frac{C}{N}]$
• $R_{total} = \sum_{i=1}^{N} r_i^{min}$; total minimal requirement for the society that is less than resource capacity *C*
• e_i: eagerness of an agent *i* and is determined as:

$$e_i = E_{total} * \frac{1 - m_i}{\sum_{i=1}^{N} 1 - m_i}$$

• $E_{total} = C - R_{total}/2$;   total eagerness of the system

• m_i : motivation factor for an agent *i* and is selected from interval (0,1). This is used to measure the extent of sacrifice (contribution towards society). An agent having larger value of the motivation factor is considered as a better one contributor means it can reduce its need to maintain the society well-being. Ideal value of this metric is one, which means reduces its eagerness to zero.

• $l_i = r_i^{min} + e_i$; total load that agent *i* is willing to put on resource

• L : total applied on the system

• *Flag*: is boolean, which is initially set to *false.*

The step-by-step procedure for the *Altruistic Decision Making Approach* (ADA) is outlined in Algorithm 1-2.

Algorithm 1.

Pseudo code *Altruistic Decision Making Approach* for agent *i,* where m_T denotes the threshold of motivation factor;

1: **while** $m_i \leq m_T$ **do**
    if ($l_i < r_i^{min}$) **then**
        if ($L < C$) **then**
            $l_i \leftarrow l_i + 1$
            $L \leftarrow L + 1$
        Else
            for each agents $j \in \Phi$ **and** $j \neq i$ **do**
                send message *update_eager (i, j, t)*
                SIG ← **receive** message *load_free*(*j, i, t* + 1)
                if SIG **is equal to** 1 **then**
                    break;
                Else
                    continue;
    else if ($r_i^{min} < l_i < r_i^{min} + e_i$) **then**
        if ($L < C$) **then**

16. **Repeat** step 4 and 5

17. **Else**

18. **for each** agents $j \in \Phi$ **do**

19. **Repeat** step 8 and 14

20. **if** ($E_{total} + R_{total} \leq C$) **then**

21. $l_i \leftarrow e_i + r_i^{min}$

22. **evaluate** $L = P \; \forall i \; l_i$

23. Flag= true

24. **if** (Flag==false) **then**

25. $l_i \leftarrow r_i^{min}$

26. **evaluate** $L = P \; \forall i \; li$

Algorithm 2 .

Update_eager(j,i,t) (Message to Agent *i* from Agent *j*).

1. $e_i \leftarrow e_i * (1 - m_i)$
2. **evaluate** $E_{total} = P \; \forall i \; e_i$
3. $m_i \leftarrow m_i + (1 - m_i)/2$ in Φ
4. **if** ($l_i > r_i^{min} + e_i$) **then**
5. **update** $l_i \leftarrow r_i^{min} + e_i$
6. **evaluate** $L = P \; \forall i \; l_i$
7. **send** *load_free*($i,j,t + 1$) with value **1**
8. **Else**
9. **send** *load_free*($i,j,t + 1$) with value **0**

Description of Algorithm.

Initially each agent *i* apply a random load l_i^0 , which is selected from interval ($1, r_i^{min}$). Thereafter, the steps executed by each agent independently are as follows:

Till its motivation factor is less than or equal to the threshold :

1. If the load applied by agent *i* is less than its minimal requirement then,
    - if the total load applied in the system does not exceeds the capacity of resource, agent *i* will increase its load by one unit followed by one unit increment in the total applied load.
    - Otherwise, proceed as follows: agent *i* send *update_eager* message to all other agents. On receiving the message, agent *j* (with highest motivation factor) will update its own eagerness, own motivation factor, and total eagerness of the system also. Afterwards, agent *j* will send *load_free* message to *i* with value 1 (if load of agent *j* is greater than its minimal requirement and eagerness) or 0 (else). Thereupon, if the value of message *load_free* (j,i,t + 1) is 1 then agent *i* further will not send any *update_eager* message, else continue.
2. If the load applied by agent *i* is less than the sum of its minimal requirement and its agerness and greater than minimal requirement then
    - follow above mentioned strategy as it is, except agent *i* send *update_eager* message to all other agents and itself too.
3. If total requirement of the system is less than the resource capacity then agent *i* will apply the load upto its total requirement (i.e., sum of its minimal requirement and eagerness) and set Flag to true.

When its motivation factor is greater than the threshold and Flag is false :

agent *i* will set its total load to minimal requirement r_i^{min} and update total load of the system.

Convergence to equilibrium.

The system reaches equilibrium when for all the agents two conditions satisfied:

(i) motivation factor of each agent reaches to threshold value, and
(ii) total requirement of the system is less than the resource capacity.

CHAPTER 5

EXPERIMENTAL RESULTS

We have proposed an algorithmic approach to solve the issue related to the Tragedy of the Commons. The Altruistic Decision Making Approach (ADA), for an analysis of the relative performance, is compared against another decentralized technique named as *Local decision procedures for the Tragedy of the Commons* (LDP) [9] to avoid the TOC. In order to ascertain strong and weak points of an algorithm, it is essential to judge its efficacy on varying parametric conditions. The parameters setting for experiments are as follows: both the algorithms are examined for four different scenarios:

(i) Number of agents in the system (*N*) is 10 and the capacity of the resource (*C*) is 100,

(ii) *N*=15; *C*=100,

(iii) *N*=30, *C*=300, and

(iv) *N*=45, *C*=300. Here,

The value of λ is taken as 1. Furthermore, the initial total load needed for the society, i.e., E_{total}+R_{total} will be greater than the resource capacity.

The variation of load for both the contestant algorithms over four different environmental conditions is depicted in Figure. 3. The Figure indicates how the autonomous agents reaches equilibrium. It is obvious from Fig. 3(a)-3(d) that after a random initial load , agents steadily increase the load on the shared resource. But, it is interesting to see that our ADA approach outperforms its competitor, i.e., LDP approach in a statistically significant fashion: (i) in ADA, the equilibrium is achieved without any danger of over utilization while in LDP approach, first over utilization occurs thereafter effort is made to achieve equilibrium, and (ii) the number of iterations required to reach equilibrium for the ADA is less than that for the LDP.

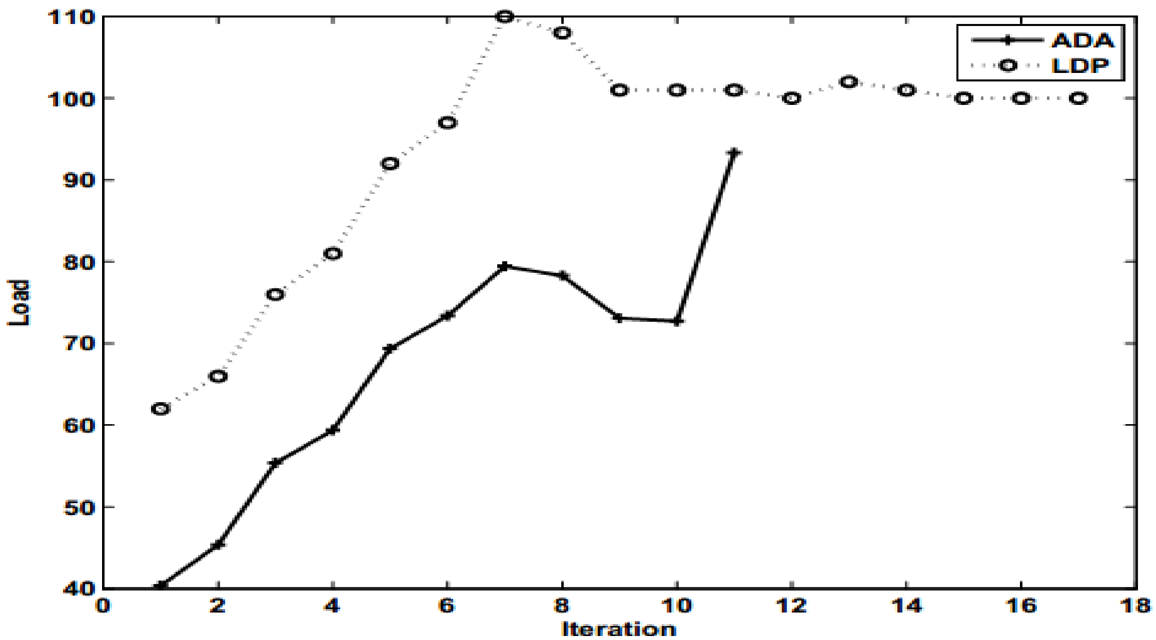

Figure 3 (a) . Load variation when N=10 and Capacity = 100

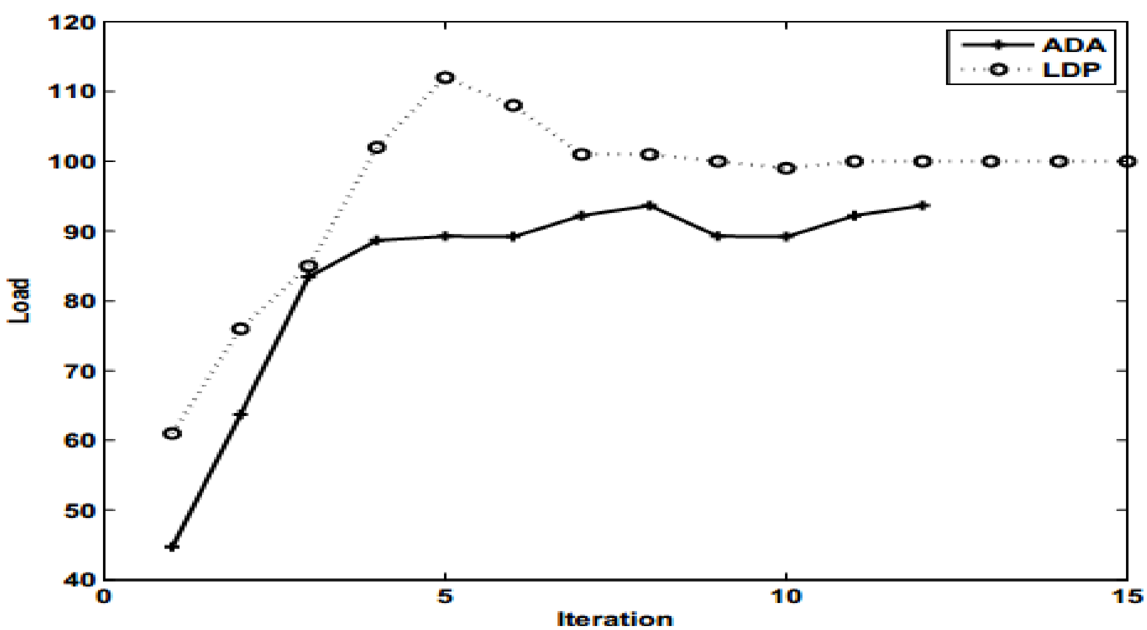

Figure 3 (b) . Load variation when N=15 and Capacity = 100

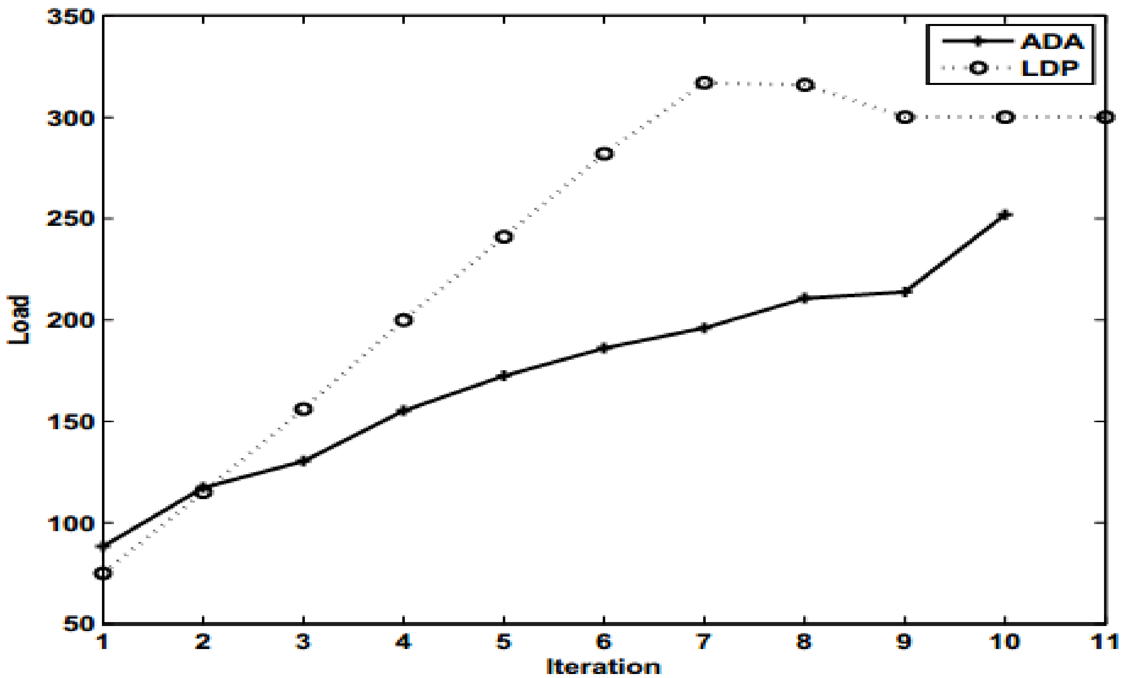

Figure 3 (c) . Load variation when N= 30 and Capacity = 300

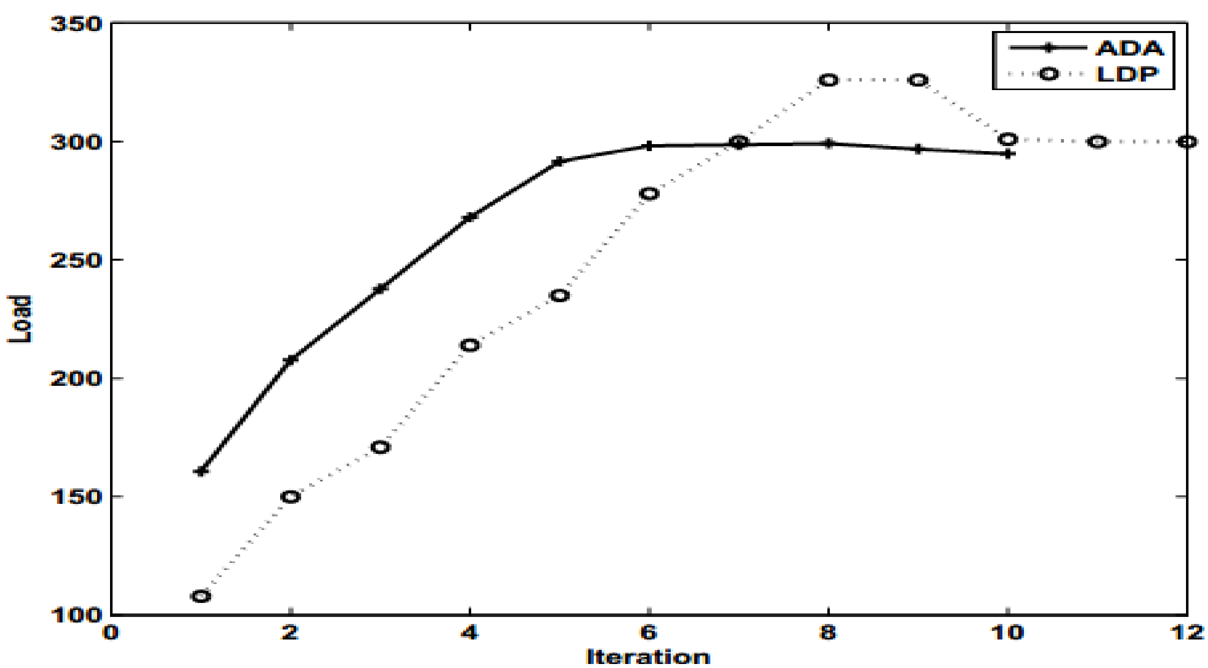

Figure 3 (d) . Load variation when N= 45 and Capacity = 300

The variation of the average per unit utility for an agent is illustrated in Figure. 4. It is clear from Figure. 4(a)-4(c) that in ADA approach agent receive a constant utility in the entire time span. In other words, there is no temptation for agents to free ride on the efforts of others since agents are socially motivated and is disposed to avoid over utilization of resource. On the contrary, in LDP, there is variation in the utility. Initially, each agents try to maximize the utility, but when load exceeds the capacity, per unit utility degrades. In last, however, optimal capacity is used at equilibrium and agents drives the maximum per unit utility.

So in Figure. 4(a)-4(c) we can notice that , the value of average per unit utility for an agent in ADA is always constant or equal to 1 as the agent never tries to overutilize the shared resource as compared to that in the other approach where the value of utility varies as each agent tries to maximizes it's utility without the social concern .

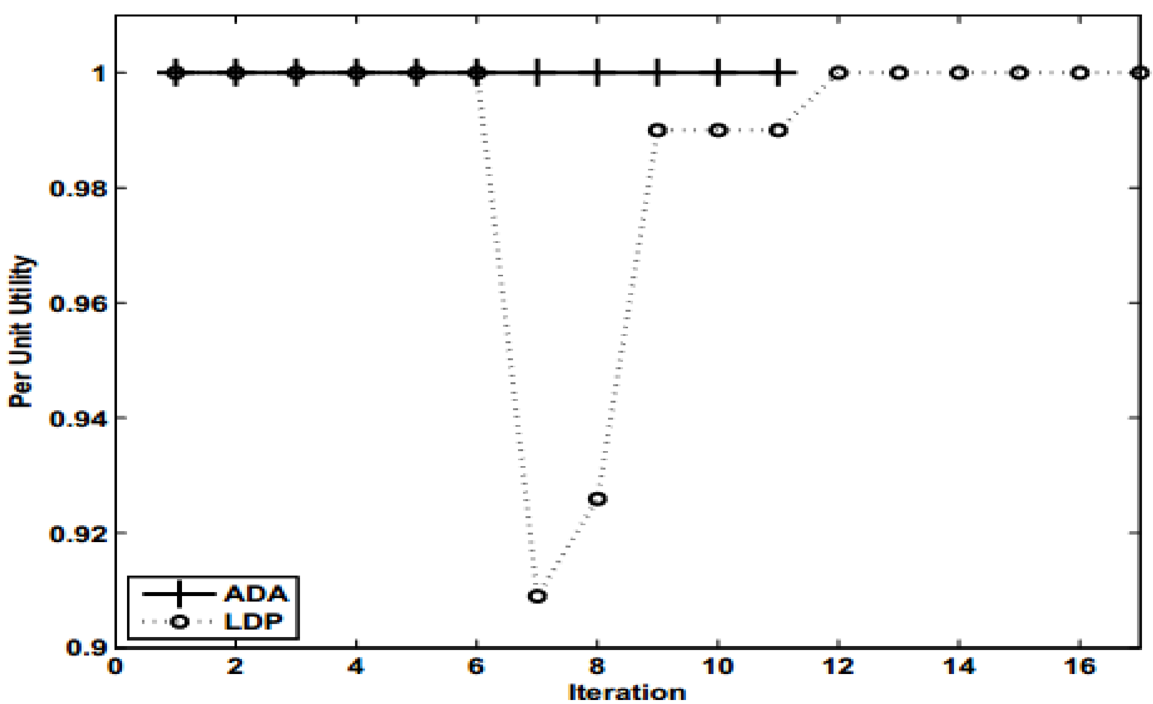

Figure. 4(a) Variation of the average per unit utility for an agent when N=10 , C =100

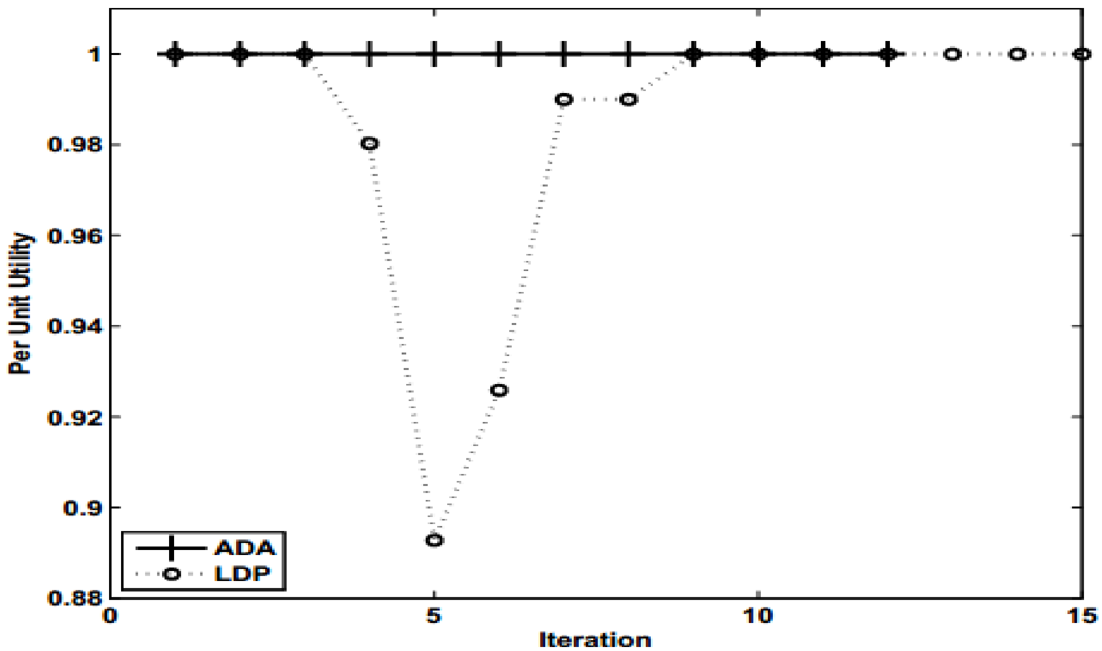

Figure. 4(b) Variation of the average per unit utility for an agent when N=15, C =100.

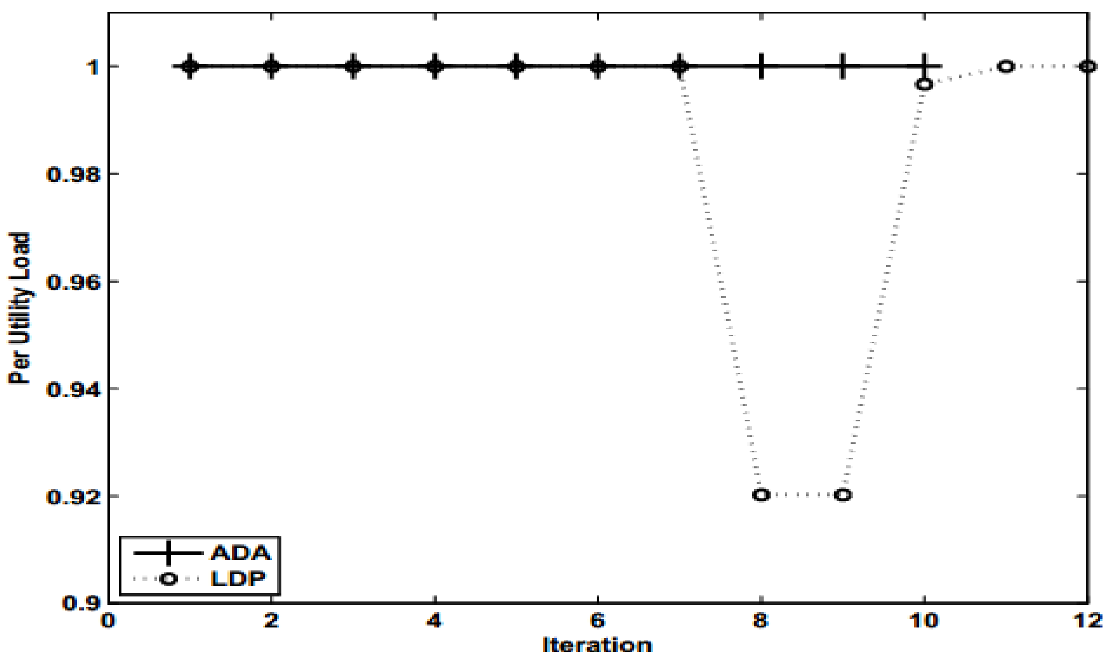

Figure 4(c) Variation of the average per unit utility for an agent when N=45, C =300.

Next, In the ADA approach, to demonstrate the dependency of agent's eagerness over its motivation factor, we plot agent's eagerness against motivation factor. This relation have been shown in Figure 5. From Fig. 5(a)-5(d), it can be seen that the eagerness of agent decreases as its motivation factor increases.

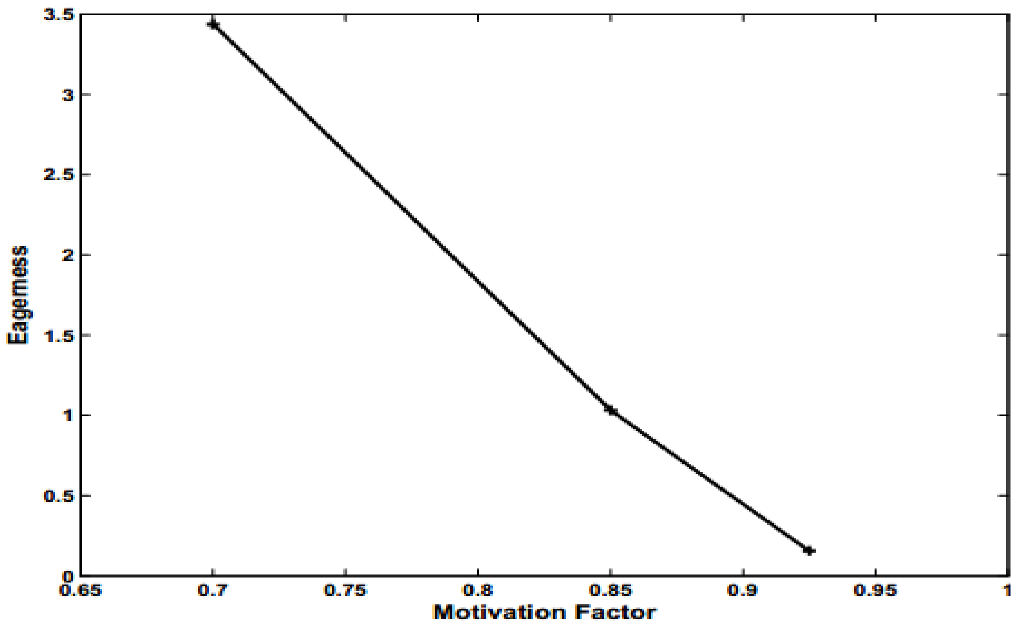

Figure 5(a) . *Variation of eagerness of an agent and it's motivation factor N=10 , C=100*

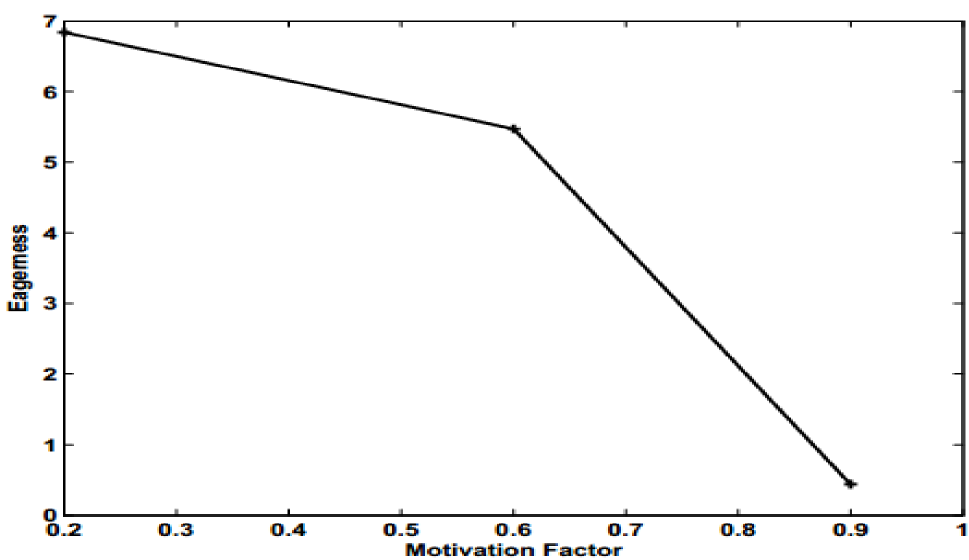

Figure 5(b). Variation of eagerness of an agent and it's motivation factor N=15, C=100

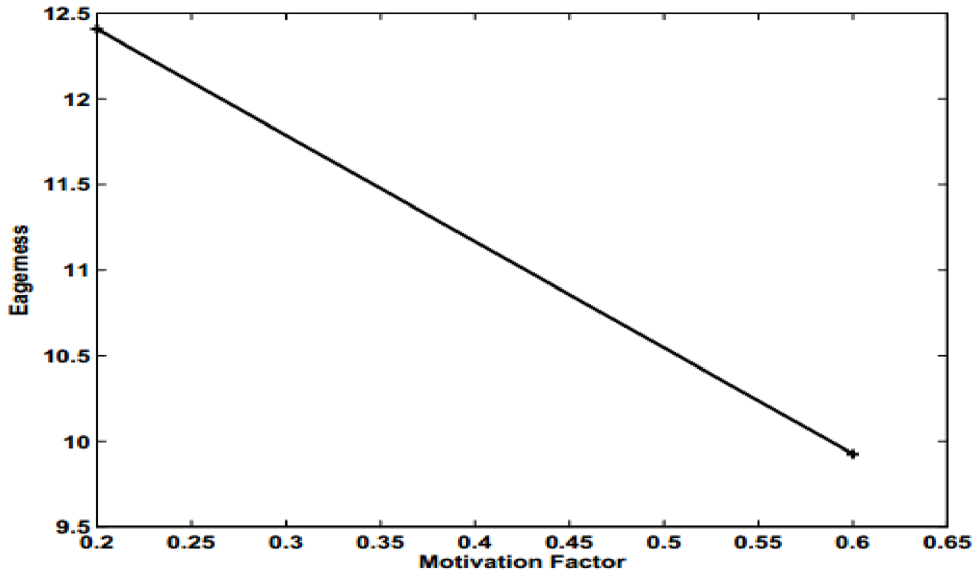

Figure 5(c). Variation of eagerness of an agent and it's motivation factor N=30, C=300

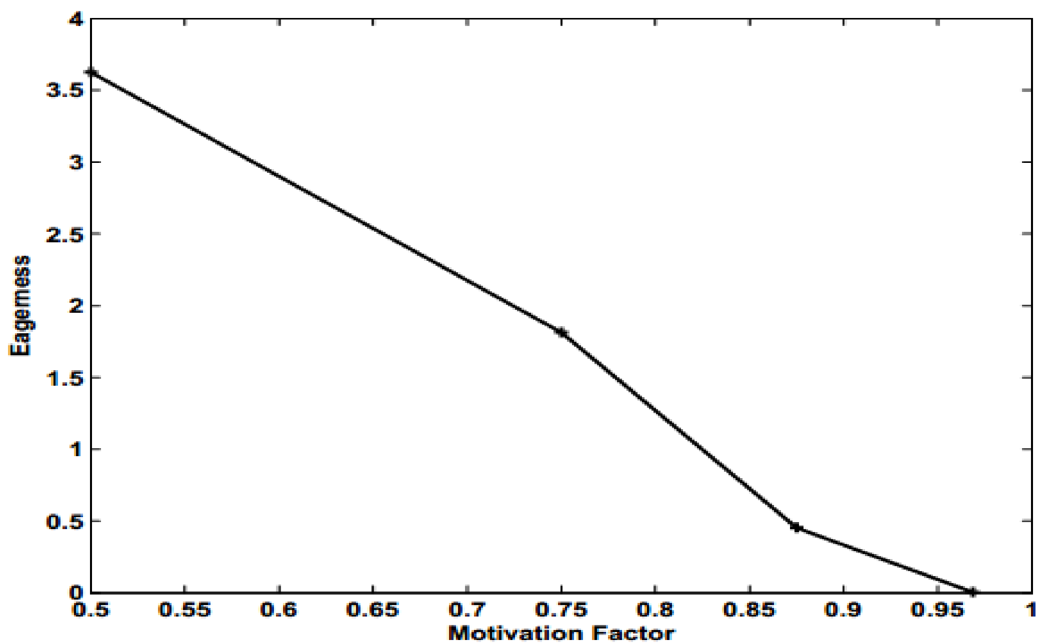

Figure 5(d). Variation of eagerness of an agent and it's motivation factor N=45, C=300

The overall experimental result evinced that our proposed ADA approach to resolve the Tragedy of the Commons problem demonstrates the superior performance in comparison to LDP approach. Finally, it will lead us to claim that the ADA is an effective approach to avoid the TOC problem.

CHAPTER 6

CONCLUSION AND FUTURE WORK

We presented a new decentralized computational approach aimed to solve the Tragedy of the Commons problem, namely *Altruistic Decision Making Approach* (ADA). In this approach, a novel decision making framework, including the motivation factor of agents, to address the decision making problem, has been devised. Agents can adjust their motivation factor as well as eagerness according to the varying dynamics of the system. Moreover, this framework does assure that the minimal requirement of all the agents will be fulfilled without harvesting the utility of others.

The performance of the ADA is compared with LDP which is another decentralized techniques, in various social scenarios. The empirical results elucidate that socially concerned decision attitudes yield better performance in resource bounded contexts than the rational, selfish attitudes. In particular, our experimental results reveal the importance of balanced decision making considering both the individual and system consequences, since there is no over utilization of resource. Therefore, it is concluded that the ADA is a simple and potential approach to solve the Tragedy of the Commons problem and is characterized by the following features. As it does not involve any complex parameter, it is easy to understand and implement. This approach can handle integral as well as real-valued loads. Finally, As opposed to other approaches to the Tragedy of Commons problem, which are centralized, we propose an inherently distributed approach.

In terms of future work, the authors are aiming to analyse how autonomous and intelligent agents can dynamically made cooperation with one another and then utilize this knowledge to develop more efficient approach.

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