博士論文

An Agent-Based Simulation of the Emergence of Societal Phenomena Using a Group Cognition Model

(グループ認知モデルを用いた社会現象の創発に関する
エージェントベースシミュレーション)

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DIPTA MAHARDHIKA

ABSTRACT

Phenomena like norms, public opinions, and social movements are based on individual actions and their interactions as the building blocks. Usually the interactions are modeled by creating some agents that are more influential than others. In this study, the emergence of such phenomena is modeled as a bottom-up process where all agents have an equal level of influence on each other. There is also no leading agent that can coordinate, reward, or punish other agents. A group-cognition model based on the concept of mutual belief and mental subgrouping is used as the basis to understand bottom-up emergence of societal phenomena in an agent society. By using the concept of mutual belief and mental subgrouping, this study attempts to model the mechanism of how individual decision making and incomplete interaction between the agents shape a societal phenomenon. 'Mutual belief' describes agents' interaction as a set of individual cognition and belief about other agent's cognition. 'Mental subgrouping' describes the strategy of aggregating such belief when there are many other agents to interact with. The model is implemented in a multi-agent simulation and norm emergence is simulated under various cognitive strategies based on the proposed model. The result shows that mental subgrouping and awareness to other agents' expectation prevent the society to overconsume common resources, even though there is no leading agent and the communication between agents are not perfect.

Keywords: *Norm emergence, Group cognition model, Multi agent simulation, Social simulation*

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

Chapter I
INTRODUCTION

1.1 Background

In a society with free (autonomous) agents, each individual agent is pursuing his/her own goal. Even though their goals are not necessarily the same (unlike teams), the pursue of one's goal can hinder other's pursue of other's goal. Therefore, a coordination between the agents is very important. Such coordination can be done in several different ways.

The most common way is by establishing an institution to control the autonomous agents. An example of this method is the establishment of a government in a country. A government creates rules to control the interaction between citizens, such as traffic rules in the case of coordinating citizens' behavior on the road. The government decides what kind of driving behavior is right or wrong. It decides which side of line the people should drive, the maximum speed, and so on. To avoid conflict, the citizens can simply follow the rule made by the government.

This method is simple and effective but may not work in all situations. One factor is the cost to enforce the law. Due to the size of the society, it may not be possible for the government to monitor the behavior of every citizen. Another factor is that people may not want to be controlled by the government in every aspect of their life.

Another method of coordination is by establishing a norm. One example is the norm to form a line while waiting. Such kind of coordination cannot be controlled by the government because it is impossible to monitor every single occasion that requires lining up. The norm to line up was probably not decided by an institution, nor the result of explicit coordination between all members of the society. Each member of the society has the option of either to defect by cutting the line or cooperate by forming the line. However, in any society usually it is quite easy to find out whether the norm is to line up or not.

Some societies may already take the line-up norm for granted. They do not need to deliberate about which action is the right thing to do (line up or not) because the norm is already established. Some other societies might think the opposite, in which not forming a line is the norm. In some countries, people get used to compete and fight to be the first in line instead of queuing. Nevertheless, in both cases, tracing back how such norm established is difficult.

There are still cases where the society is still struggling in establishing a norm to coordinate the action of all society members. Innovations in industry force the society to create a new norm in handling new problems caused by those innovations. Online social media is one example of this kind of problem.

Social media is a relatively new phenomenon. It allows people to interact anonymously and asynchronously. Such a method of interaction triggers many problems, such as the Online Disinhibition Effect (ODE), where people tend to behave more intensely than they would in person (Suler, 2005).

There are many serious cases of ODE. In 2013, Justine Sacco, a senior director of an internet company jokingly wrote a tweet about her trip to Africa and AIDS. The tweet went viral and was responded angrily since many people thought it was offensive and racist. She lost her job afterwards. Being online made her feel that she could be more freely in expressing her thought (Ronson, 2015). Similar other cases are Adria Richards cases in PyCon Technology Conference 2013 (Ronson, 2015) and Florence, a student in Jogjakarta, Indonesia, where she posted an offensive tweet about the city in 2014 (Rakusen, Devichand, Sampat, & Susilo, 2014). There was no norm about what can and cannot be posted online, in those cases they just did what they thought was fine. Other cases are about impolite comments, or other offensive remarks in online social media. Recently there are also cases about fake news and hoaxes online, especially related to political event (BBC Asia, 2017). There are no norms about the politeness level or about whether it is acceptable or not to write fake news. People behave by only following their own intentions.

Determining a law for cases in the internet is not easy. One reason is the jurisdiction. Since such cases do not happen in a particular physical space, it is difficult to define the jurisdiction. Other reasons are that most of the cases are not criminal activity, so the law cannot punish them. The internet is also too huge to be controlled by a certain institution. However, a guideline is indispensable to guide the users what to do while using the internet.

The struggle to find a guideline in determining what is the correct thing to do is no longer an exclusive domain of human agent. Recently there are many smart and autonomous devices invented and produced. One popular example is the self-driving car. Self-driving car is designed to response to its environment and react accordingly. In the future, it is visioned that those cars will coordinate with each other, instead of only responding to its environment (Furda & Vlacic, 2009). The problem with that goal is that not every possible situation of interaction and coordination can be decided by design. For example, the self-driving cars may need to coordinate with each other in determining what is the proper speed limit in general. We might be able to learn from how human coordinate with each other to decide what is the right thing to do, and implement the mechanism into the autonomous agent-society.

Such guidelines may come up as norms. Norms are societal phenomena that facilitate coordination and cooperation among the members of a society. Norms can be loosely defined as the understanding of what is the right thing to do given a certain situation. It is a mental representation of the appropriate behavior, and plays a role as a guidance for people to act (Aarts & Dijksterhuis, 2003). Sometimes norm is confused with the notion of moral virtue, which is based on the sense of what is right or wrong. However, there are cases where people understand what should be done in a certain situation by observing what other people do in the same situation, even without knowing the morally right thing to do (e.g. Goldstein, Cialdini, & Griskevicius, 2008). Moral virtue is usually difficult to predict without knowing the base on which the judgment of right or wrong is made, such as rule of law or religion. Cialdini (2009) mentioned that in the case where there is no clear guidance on what to do, people usually look for clues from other people's behavior. Moreover, people tend to think that what the majority does is the right thing to do. (Further discussion about the definition of norms can be found in Section 2.3)

In many cases, norms are not created as a prescription from an authority (top-down), but rather emerge as the result of the interaction between the members (bottom-up). Coleman (1990) mentioned that norms are a macro level (societal) construct based on micro level (individual) actions. They come into existence through a micro-to-macro transition. It is impossible and might not be desirable, for an authority, government for example, to create a rule and guidance for everything about the daily lives of the society. Many of society's aspects of life are self-governed.

1.2 Multi-Agent Simulation Based on Cognitive Model

1.2.1 Top-down and bottom-up emergence

Performing a large-scale experiment to see how norms are formed in a society is difficult. We cannot create a new society of many agents that has no institutions or government and see how they form a new norm. It is also difficult to isolate factors to see their effect on the emergence of norm. Computer simulation has been used to understand the phenomenon since 1980s. Researchers use simulations to test their intuition about norms (Neumann, 2010). Norm simulation is usually done in a multi-agent system. The term NorMAS (Normative Multi Agent System) is usually used to describe such system (Savarimuthu & Cranefield, 2011).

From the perspective of how a norm emerges, NorMAS can be categorized into top-down and bottom-up emergence. In the top-down mechanism, it is assumed that there is already one correct norm in the society. Some superior agents create the norm by using norm creation mechanism. Other agents will then detect the norm and apply it to themselves. Some agents will also spread the norm to others, and even sanction them. This perspective requires the assumption that some agents are initially superior to the others. In this perspective, norm is seen as a micro level phenomenon which is later *scaled up to* the whole society to make it a macro level phenomenon. The norm is said to have emerged after it has been adopted by a certain number of agents (Hollander & Wu, 2011). Such a process adopts a top-down mechanism of the emergence of societal phenomena (Figure I-1).

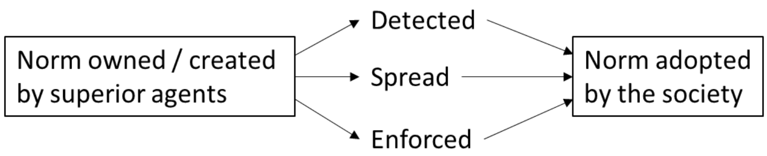

Figure I-1. Top-down emergence of norm (as published in Mahardhika, Kanno, & Furuta (2017))

Based on Coleman's (1990) argument, norms should come into existence in the transition process between micro and macro level. In the micro level, no agent possesses any norm. They have their choice of actions, but these actions are not the norm until the actions undergo a transition process. If this argument is to be followed carefully, emergence of norms should focus on this transition process. If it is used as the underlying assumption, all agents can be assumed as equal because we do not need superior agents to create, spread, and enforce the norms. Such process adopts a bottom-up mechanism of the emergence of societal phenomena (Figure I-2).

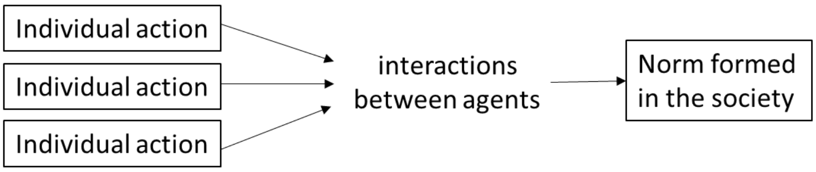

Figure I-2. Bottom-up emergence of norm (as published in Mahardhika, et.al. (2017))

1.2.2 Group cognition model

Several different models have been proposed to study norm emergence using NorMAS. Most of the models are based on game-theory (Axelrod, 1986; Sen & Airiau, 2007). Using such an approach allows researcher to understand the fundamental process behind the phenomena by only using a simple model. Axelrod (1997) used the term KISS (keep it simple, stupid!) to refer to such an approach.

However, Terano (2008) argues that even though KISS approach gives the flexibility to researcher in implementing the model and at the same time can give a powerful insight, it has its own disadvantage. He argues that the simpler the model, the more explanatory interpretation is necessary. To better understand the mechanism of societal, researchers should aim not to a simple model, but to find the right trade-off between simplicity and explanatory power.

Game theory approach like the 'prisoner's dilemma' game uses one fundamental assumption in explaining the agent's decision making. The assumption is that the only thing the agents want is to make maximum profit, given several choices of possible strategies. Such a model cannot explain other possible factor in agent's decision making such as the desire to conform, or different perception of agent's toward the norm.

Andrighetto et al. (2007; 2010) proposed a cognitive architecture in modeling the agents in a norm emergence simulation. This model puts more complexity to better resemble the cognitive mechanism in the agent's decision making. Their architecture is called EMIL (Emergence in The Loop). They focused on a process called norm internalization. They mentioned that for an agent to obey a norm, it has to not just recognize it but also internalize to make it the drive of its action.

The fundamental building block of societal phenomena is individual human cognition, such as intention, decision, and action. To explain the emergence of norm from this building block, it is necessary to use a model that can explain both the individual cognitive processes, the interaction between the individuals, and the emergence of the norm. A group cognition model can be used for this purpose.

One example of group cognition model is a model called mutual belief model (Kanno, Furuta, & Kitahara, 2013; Mahardhika, Kanno, & Furuta, 2016). This model can explain a group cognition from its building blocks, which are the individual cognitive processes and the interaction between them. The interaction between the individuals is represented by a so-called 'belief' among the agents. The modeling approach by reducing the higher level process (group cognition) into its building blocks (individual cognition) is called reductivist point of view (Chant & Ernst, 2007).

1.3 Objective of This Study

As mentioned in Section 1.1, people need guidelines on how to behave when there is new technological innovations such as the internet. As an explicit rule of law may not be enough to control social media, intervention may need to be done by other institution such as the social media company. However, to know what kind intervention is proper, it will be necessary to understand the mechanism of how the member of the society, in this case, the users of the internet, form a norm.

Specifically, a particular factor to be understood is how a society can form a norm with the limited cognitive capability. A limited cognitive capability hinders the agent to communicate with *all* members of the society. Even when they communicate with a portion of the society, they may not be able to communicate their observation to other agents. To understand this, we need to observe emergence of norm using a model that models societal cognition in their basic building blocks, which is individual cognition.

To explain the emergence of norms from their basic building blocks, a new approach in NorMAS is required. In line with Coleman's (1990) definition, a bottom-up emergence model is more proper in representing the emergence of a norm in a society. A cognitive modeling is also required to explain both the individual agent's decision making process, and the micro-to-macro transition into the norm.

Thus, the objective of this research is defined as follows. This study aims to understand the mechanism of norm emergence by analyzing the transition process between individual actions into the society's norm. In particular, a group cognition model is used to represent the individual cognition (actions, intentions) and their interaction. The model is implemented in a multi-agent simulation.

1.4 Structure of Thesis

In this chapter, a brief introduction about the research has been given to explain the motivation behind the research. In Chapter II, a detailed theoretical study covering human cognition theory and the studies about norm are presented. It also includes the comparison with the current study. Chapter III presents the model of norm emergence proposed by this research. This includes the adaptation of the mutual belief model to the norm emergence phenomenon. Chapter IV presents the detail of the simulation, including the result and the discussion about the result. Chapter V explains the limitation of the current study and suggestions for future research. Chapter VI presents the conclusion of the study.

Chapter II
LITERATURE STUDY

2.1 Levels of Human Cognition Study

The studies of human cognition can be divided into three different levels: micro level, meso-level, and macro level. The micro level studies the cognition of individual human. The meso-level studies cognition in the level of a small group or team. The macro level studies cognition in a larger scale, i.e., a society. A distinct feature of the macro level compared to the meso-level is that each member cannot interact with all of other members, but only a portion of it.

2.1.1 Micro level (individual)

In the micro level, human cognition study deals with phenomena such as perception, memory, and individual decision making (Matlin, 2012). The study seeks to understand how humans behave and respond to stimulations from their environment. By understanding this, we can help people increase their individual performance, for example by avoiding human error. For example, it is well known that humans do not always make a rational decision. In most of the time, humans use a so-called System 1, a quick thinking process, instead of a slower but more logical System 2 (Kahneman, 2011). Understanding this difference will help people avoid biases and errors.

2.1.2 Meso-level (group / team)

As a social organism, it is very natural for humans to interact with each other. Cooperation between humans allows many great achievements that otherwise could not be achieved individually. The studies about human cognition in regards to the relation with each other can be divided into two levels: meso-level (group / team) and macro-level (societal).

An entity with more than one person in it can be called a social-aggregates (Forsyth, 2010). Lickel, et. al. (2000) listed four different types of social aggregates: primary group, social group, collectives, and categories. By looking at the different characteristics of those aggregates in the aspects of social tie, permeability, and time span, Mahardhika and Kanno (2016) classifies primary group and social group into “group”, and collectives and categories as “society”.

Primary group refers to an intimate cluster of close associates, such as families, or close friends. This kind of groups tends to have intensive interactions, and those are mostly for maintaining the intimate relationship. The size of a primary group is usually small. On the other hand, a social group tends to be larger and less intimate than a primary group. This kind of group is often task oriented. Some examples are sports group, fraternities, military squads, companies, and so on.

Collectives are usually large, spontaneous social aggregates. The members have a loose or no emotional relationship, and are usually strangers to each other. However, they are tied to each other by spatial proximity, common rules, norms, or a purpose. Some examples are audience of a concert, queue, riot, and so on.

Social categories are similar to collectives in that the members have no emotional relationship. However, they are tied by their similarities or common features, such as interest or cultural background. Some examples are Americans, women, fans of a certain music group, and so on. It is important to note that if a social category does not have a social implication to a 'member', then this is not regarded as a social aggregate for this particular 'member'. If the presence of that category influence a member's behavior towards other members or any person outside the category, then it can be called a social aggregate.

The difference between a group and a society is not just about their size. The other differences are the degree of how much the individual members know about other members personally (social tie), their interactions, their timespan, and their permeability (Mahardhika & Kanno, 2016). In the case of a group, it is reasonable to assume that everybody knows everybody, or at least most of them. Every interaction done between members is recognized as interaction with a particular person(s) that they know. When they exchange some information, the information receiver may care about both the content of the information and who the information provider is. Each of the member is connected in a socially meaningful way.

Social tie is indicated by more communication in the relation dimension than in the task dimension (or at least balanced communication in those two dimensions). This is important to maintain the social tie among the members. It is well recognized in the field of team science that both relation-oriented and task-oriented communication are important for the team performance (see, for example, Mohammed, Ferzandi, & Hamilton (2010)).

In the case of a society, the members do not know each other. Interactions in a society are content oriented or transactional, since there is no social tie to maintain. When there is an information exchange between members, the receiver may only care about the content of the information and not about the information provider (who the provider is, and so on).

One factor that causes the lack of social tie in society is their size. As the number of people inside a social aggregate increases, the number of possible interaction increases significantly. Since it is difficult to maintain many interactions, it is very natural that in larger aggregates, the members will have more difficulty in interacting will other members.

Researches in the meso-level deals with some phenomena such as social influence, group decision making, team performance, and so on. The relationship between micro and meso-level can be explained well using reductivist point of view (Chant & Ernst, 2007; Tuomela, 2007). This point of view reduces cognition of a group into the cognition of its members, and a certain relationship between them. The relationship can be explained by using a concept called mutual belief. The detail of this concept is explained in Section 2.2.

2.1.3 Macro level (societal)

Due to its distinct characteristics from the meso-level, there are some phenomena that occurs only in the macro-level. Some examples are norms, public opinion, trends, and crowd behavior.

Norm is a guideline about what is right or wrong that is understood by the members of the society. The example of norm is the norm to queue when waiting for a train. Definition of norm is explained further in Section 2.3.

The term "public opinion" is usually used in the political field. It refers to the collective opinion of the people of a society regarding an issue in the society (Bianco & Canon, 2013). Trends refer to a change in opinions, behavior, lifestyle of a large number of dispersed individuals (Forsyth, 2010). One example of trend is fashion trends. A certain type of fashion can be popular among many individuals in a certain point of time.

When many people share a common location and when they have a common focus of attention, they become a crowd (Milgram & Toch, 1969). Le Bon (1960) was the first to mention that when humans are in crowd, it seems that a sort of 'collective mind' emerges that makes their behavior different from that when they are alone. Researchers agree that this phenomena is triggered by human emotion (as opposed to rational consideration) (Blumer, 1951; Freud, 1921). In the extreme cases, human emotion can be accumulated to form a different type of crowd which are the panic (triggered by fear), the craze (triggered by joy), and hostile outburst (triggered by anger) (Lofland, 1985).

In the field of social sciences, there are several theories of how macro phenomena can happen. They are contagion theory, convergence theory, emergent-norm theory, and value added theory.

Contagion theory says that a large number of people can have a hypnotic influence to affect individual action even though initially the individuals do not share a same intention (Le Bon, 1960). On the other hand, convergence theory says that societal phenomena happen because initially people with similar intention comes together (Dollard & Miller, 1943). Emergent-norm theory emphasizes that the members of a large social aggregate initially have different interests and motives. When the members find a vague situation, they will always search for a norm (Turner & Killian, 1993). In the value-added theory, Smelser (Smelser, 1962) argues that collective behavior is a kind of "tension release" within the society. In this sense, he argues that the members of the society already have an intention to do the collective behavior, but it requires a trigger for that behavior to occur.

In the current study, we want to explore further the mechanism of the emergent-norm theory. We want to use the reductivist point of view to see the relation between individual cognition, their interaction, and the emergence of norms.

2.2 Mutual Belief Model and Mental Subgrouping

One group cognition model that uses the reductivist point of view is the mutual belief model (Kanno, Furuta, & Kitahara, 2013; Mahardhika et al., 2016).

The model describes 'group cognition' as a set of three layers of mental construct and cognitive processes, distributed in each group-member's mind. To explain the structure of the model, a group of three members namely A, B, and C is assumed. Figure II-1 shows the schematic representation of A's part of the team cognition. Figure II-2 shows the schematic diagram for the whole group.

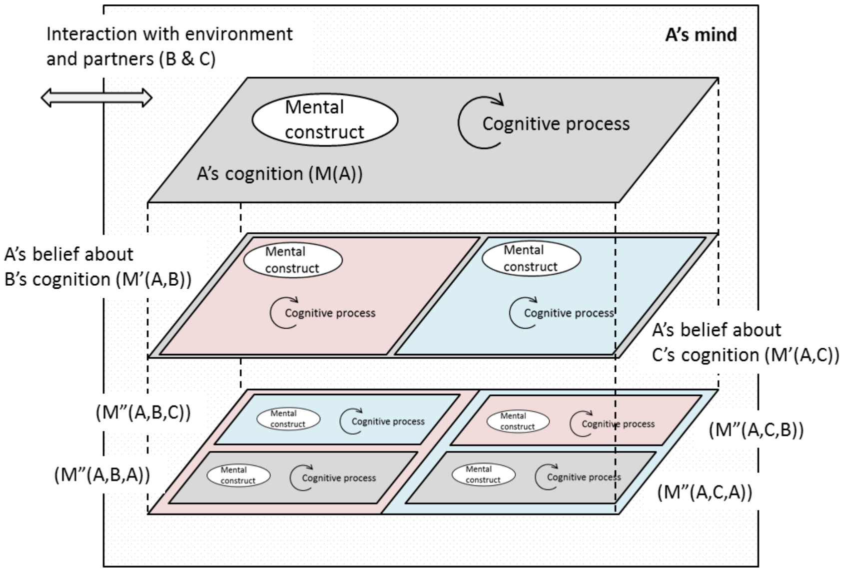

Figure II-1. Mutual belief model (individual)
(source: (Mahardhika et al., 2016)**)**

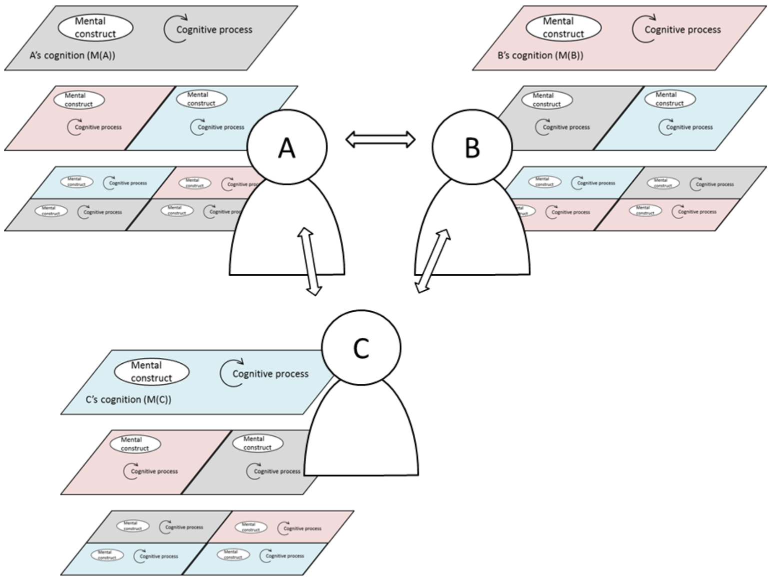

Figure II-2. Mutual belief model (group)
(source: (Mahardhika et al., 2016)**)**

In Figure II-1, the first layer, namely self-cognition layer, contains A's own cognition excluding belief about other partner's cognition. This can include A's situation awareness, intention, emotion, perception, etc.

The second layer, namely direct belief layer, contains A's belief about his/her partners' cognition. This layer is divided into smaller parts called blocks. Each block contains A's belief about each partner's cognition, which does not include belief about partner's belief. This may include what A believes about B's and C's perception, thoughts, emotion, intention, and so on. Because in this case we assume a group of three persons, thus A has two partners, hence two blocks in the direct belief layer. The number of blocks is always *n-1* where *n* is the group size.

The third layer is called projected belief layer. This layer consists of several blocks, explained as follows. In each column exists two blocks (*n-1*). For example, if the column on the left of direct belief layer represents *what A believes about B's cognition*, then the blocks on the left column of projected belief layer represents *what A believes about what B believes about C/A's cognition*. The right column contains *what A believes about what C believes about B/A's cognition*. The bottommost row of this layer contains A's belief of belief about A's own cognition. For example, the left bottom block is A's belief of B's belief about A's cognition. In the same way, the right bottom block is A's belief of C's belief about A's cognition. The row(s) other than the bottommost row contains one's belief of partner's belief about the other partner's cognition, such as *what A believes about what B believes about C's cognition* (left top block). Totally projected belief layer has $(n\text{-}1)^2$ blocks, where n is the size of the group.

Theoretically, the number of layers can be more than three (such as the belief of belief of belief of someone's cognition). However, three layers are already enough to explain human interaction (Kanno, Furuta, & Kitahara, 2013). In a normal situation, people do not even pay attention to the status of the third layer (Mahardhika et al., 2016). Besides, it also has been proved that average humans can only handle maximum around five layers of such structure (Stiller & Dunbar, 2007).

When the size of a group increases, the number of blocks in layer two and three also increases rapidly. To handle this problem, there is a process called 'mental subgrouping' (Mahardhika, et. al., 2016). 'Mental subgrouping' is defined as a mental action in individual's mind of treating several persons as a single entity. It has been proven that this is an inherent process in human's mind. When people interact with one other, they almost always create a mental subgroup. Mental subgrouping was observed by the usage of plural personal pronouns such as they, we, their, us, and so on.

Mahardhika, et. al. (2016) defined one type of mental subgrouping in the direct belief layer ('What I believe about their cognition'), and five types in the projected belief layer. The difference between those types is whether the entities are plural or singular. Some examples are 'What I believe he believes about our cognition', 'What I believe they believe about each other's cognition', and so on.

Like the cognition of a group, the current study also wants to view the cognition of a society using the reductivist point of view. The structure of the mutual belief model can be used as it is, without any modification. The important characteristic of a society is the huge number of partners, thus a large number of blocks in the second and third layer of the model. Besides, since the agent cannot be aware of all other agents in the society, mental subgrouping process will happen. Thus, in the case of societal cognition, the second layer represents 'What I believe about the society's cognition'. The third layer represents 'What I believe the society believes about the society's cognition.' Since the agent is also part of the society, the third layer implicitly represents 'What I believe the society believes of my cognition'.

One different feature between group cognition and societal cognition is in the way the mental subgrouping is formed. In the case of a group, the agents can interact with all other agents. From that interaction, the information that the agent gets about other members' cognition is grouped into several mental subgroups. In the case of society, the agent can only interact with a portion of the society. To infer the cognition of the whole society (as a mental subgroup), the agent can only use the information from the members that it can interact with. In real life, this situation can be observed when people mention a stereotype of a certain society. For example, people can say "Japanese people likes to wait orderly in line", even though he or she has not met *all* Japanese people.

In the emergence of societal phenomena such as norm, each agent in the society will try to perceive the expectation of the society. But since they can only interact or observe with some of the society's member, in their view, the expectation of the society is represented by these few members.

The advantage of using mutual belief model to represent cognition of the society is the possibility to explain the society's cognition both in outsider's perspective and also the perspective of the agent itself.

2.3 Definition of Norms

In this research, norms are chosen as a study case to represent other societal phenomena. The aspect that we want to explore is the emergence of the societal phenomena by using the reductivist perspective. In this sense, even though norms and other societal like public opinion or crowd behavior have different definitions, they still share one same feature. Those phenomena are still composed by the decisions and actions of the individual members, thus can be analyzed using the reductivist perspective.

According to Oxford Learners Dictionary, norms are "standards of behavior that are typical of or accepted within a particular group or society" (Bradbery, Turnbull, & Deuter, 1948). Cialdini and Trost (1998) emphasize the feature that norms are understood by society members and guide their behavior *without the force of the law*. In the same nuance, Melnyk (2011) defines norms as "informal rules and standard". He also mentioned that one important element of norms is the social reinforcement.

Bicchieri (2006) proposed a '*rational reconstruction*' of what social norm is. In her definition, an agent will follow a norm when a 'conditional preference' is met. This preference consists of two types of expectation. One is called *empirical expectation*. This is an expectation where the agent believes that a sufficiently large people in the society will follow that norm. The second is called *normative expectations*. This is an expectation where the agent believes that a sufficiently large people in the society expect the agent to follow the norm. It is important to note that the "sufficiently large number" is a subjective condition, and can also be different between different norms and contexts.

The term '*emerge*' or '*emergence*' is also an important element in the discussion about norms. Norms are considered emerged when it has been adopted by an adequate number of agents in the society. However, it is difficult to decide the threshold of how big this '*adequate number of agents*' is. In this study, instead of deciding a threshold and see whether norms have passed that or not, we will see if the moment of norm emergence is distinctively visible in the simulation process (i.e., as an abrupt change), or not.

2.4 Simulation of Norm Emergence

The mechanisms of norm emergence simulation are usually divided based on their phases in the norm life-cycle. They are creation, identification (also called 'detection' or ‘recognition’), spreading, and enforcement (Savarimuthu & Cranefield, 2011). Some recent researches can also be categorized into new categories such as norm internalization, norm assimilation, and norm removal (Mahmoud, Ahmad, Zaliman, Yusoff, & Mustapha, 2014).

There are three mechanisms of norm creation. The first is offline design, where the agents are already equipped with some norms before the simulation starts (Hales, 2002; Savarimuthu, Cranefield, Purvis, & Purvis, 2010). This approach might not be realistic, since humans may not be equipped with a norm before they interact with each other. The second is by social power. In this mechanism, only some agents in the society are equipped with norms beforehand. They can enforce the norm to other agents in the society (Verhagen, 2001). This better represents the reality, because in real life there are some institutions or authorities that decide rules and enforce people to follow them. However, as mentioned previously, many of societal phenomena are self-governed. This is represented by the third mechanism of norm creation: autonomous innovation. The simulations that use this mechanism focus on how agents generate their own idea that later can become the norm of the society. This approach is implemented by using off-line design of ideas combined by a filtering mechanism (Hollander & Wu, 2011).

Norm detection is one of the main challenges in norms simulation (Mahmoud et al., 2014). Norm detection is the agents’ ability to discover the norm in the society. There are two major types of mechanism in norm detection. The first is learning, such as imitation (Epstein, 2001) and social learning (Sen & Airiau, 2007). This mechanism let the agents learn from their environment about the right thing to do. The social learning is usually implemented by using machine learning or game theory approaches (Savarimuthu & Cranefield, 2011).

The second mechanism of norm detection is cognition. Such approach focuses on what happens inside the agent’s mind while deliberating about the norm (Andrighetto et al., 2007; Mahmoud et al., 2014).

Norm spreading deals with how a norm is distributed in the society. One area of focus is the relationship between agents, which reflects how the norm is passed from one agent to another (Chalub, Santos, & Pacheco, 2006). Another area is the network topology. They are categorized into static network topology and dynamic network topology (Savarimuthu & Cranefield, 2011).

Norm enforcement discusses how the society sanctions the agents in order to maintain the norm. It is implemented by either indirect sanctions (like reputation) (Hales, 2002) or direct sanctions (like material punishment or rewards) (Axelrod, 1986).

As discussed in Section 1.1, the above mechanisms assume that there are superior agents in the society. The most basic form of superior agents is the agents that can punish or reward the other agents (e.g., Axelrod, 1986; Savarimuthu, Purvis, Purvis, & Cranefield, 2009). Such agents are equipped with a confidence that their action is the norm that should be enforced. There are other forms of superior agents. Boman (1999) used a central advisor role in the simulation. The agents need to consult this advisor agent before deciding an action. Hoffman (2003) used the term 'norm entrepreneur' to call the agents that pick a certain action then suggest it to other agents. Savarimuthu, et. al. (2008) used a slightly different approach. He adopts a different approach by giving all the agents initial different norms. However, in the interaction process some agents will be an advisor for others, thus more influential in the society's norm emergence as a whole. In all of these situations, the interaction between agents becomes unequal.

Sen and Airiau (2007) proposed mechanism that adopts a bottom-up emergence mechanism of norms. Their model focused on the agent's social learning through experience. The society in their simulation need to create a norm of whether to drive on the left or on the right side of the road. By using machine learning algorithm, the agents try to learn the consequences of their actions and choose the safest action.

In the terms of frameworks, there are several major frameworks used in norm simulation (Mahmoud et al., 2014).

One of them is BOID Normative Architecture. BOID stands for Belief, Obligation, Intention, and Desire, proposed by Broersen, et. al. (2001). The basic mechanism of agents in this architecture is by generating goal sets after monitoring the environment. The agent's deliberation process is modeled by modeling their desires, obligations, and intentions. The advantage of this framework is that it is able to model different personality such as simple minded, selfish, or social agents.

Other framework is normative KGP agents. KGP stands for Knowledge, Goals, and Plans. Sadri, et.al. (2006) presented a framework that demonstrates how obligation and prohibition can be used by an agent while it reasons, reacts, plans, and communicates in the context of an artificial society.

Ahmad et.al. (2011) proposed another normative framework called OP-RND (Obligation-Prohibition-Recommended-Neutrality-Disliked). Basically, those elements allow the agents to give reward or penalty to other agents.

Besides norm framework, normative-agent-based system can also be distinguished by how it represents the norm. Hollander and Wu (2011) mentioned that there are four major representation schemes that have been used in representing norms in agent-based simulations.

The first is the representation as deontic logic. Deontic logic is concerned with obligation, permission, and prohibition (Meyer & Wieringa, 1994; Von Wright, 1951).

The second type of representation is the rule based systems. This is a set of condition – action pairs embedded inside the agents' decision making procedure. This is usually used in the offline-design of norm creation (Castelfranchi, Conte, & Paolucci, 1998; Hales, 2002; Saam & Harrer, 1999).

The third is a representation by using binary strings. Digit ones represent the occurrence and digit zeros represent the absence of a norm. This format is often used in research on population to test the transmission and emergence of norms (Epstein, 2001; Nakamaru & Levin, 2004).

Lastly, one common way to represent norms in an agent society is by using game-theory. In game-theory, every agent makes a simple choice of strategy that yields a corresponding payoff. Their goal is to maximize their payoff (Andrighetto et al., 2010; Savarimuthu et al., 2009).

2.5 Position of The Current Study

In this section, the summary of the model proposed in this study is presented. The key points are summarized in the following table.

Table II-1. Position of the current study

Elements	State of The Art	Current Study
Definition of Norm	Bicchieri's definition (2006)	Bicchieri's definition (2006)
Norm Simulation Architecture	BOID, KGP, OP-RND, etc.	Mutual Belief Model
Representation of Norm	Deontic logic, game theory, etc.	Intention and expectation (agent-level) Convergence of actions (society level)
Cognitive Structure	EMIL (Norm Internalization model), series of rules in norm identification	Mutual belief and mental subgrouping (a generic cognition model)
Emergence Mechanism	Top-down emergence, bottom-up emergence with superior agents, or bottom-up emergence with limited norm candidates	Bottom-up emergence, with no superior agent, with multiple norm candidates
Motivation to conform	Avoid punishment, getting reward, or norm internalization (EMIL)	Trade-off between utilitarian motive and conformity with the majority

2.5.1 Representation of norms

There are several key novelties in the current norm emergence modeling compared to the existing ones. First, in the terms of norm representation. In Section 2.4, four different types of norm representation have been explained, i.e., deontic logic, rule based systems, binary strings, and game theory. In the current study, in the agent-level, norm is represented by the combination of intention, empirical expectation, and normative expectation. This satisfies Bicchieri's definition of norms (Cristina Bicchieri, 2006). In the societal level, norm is represented as the convergence of the agent's actions. This representation allows to view norms from the subjective perspective rather than objective perspective. Different people in the same society can have different view about what the norm is. The emergence of norms is indicated by the convergence of the agents' actions, not by whether a threshold of the number of people that follow a norm has been passed or not.

2.5.2 Structure of cognition model

The second novelty is related to the model of the agents' cognition. In several different researches, norm emergence has been modeled by also taking into account the cognitive model of the agents. Andrighetto, et.al. (2010) introduced a cognitive model of norm emergence named EMIL (Emergence in The Loop). In this model he emphasized the norm internalization process. Savarimuthu,et.al. (2010) also introduced a cognitive model of norm. Their model focuses on norm identification. They represent norm identification by using a series of rules.

The model proposed in the current study differs with those two cognitive models in two ways. The first is that our model provides a reductivist point view. In this point of view, cognition of the society can be reduced into individual cognition and a relation between them. This is reached by providing a clear separation between the individual intention, the partners' intention, and the beliefs about partners' intention. In other cognitive model, such separation cannot be made.

The second difference is that our model is a generic cognition model. Our model provides a generic structure of human cognition when interact with other people. This model can be applied to other cognitive phenomena other than norm emergence. In previous researches, the same model has been used for analyzing team interaction (Kanno, Furuta, & Kitahara, 2013; Mahardhika et al., 2016) and to analyze perception gap (Kanno, Furuta, & Chou, 2013). Due to its generic characteristics, expanding the current model by adding other factor such as emotion can be done easily within the same three-layer structure. Besides, by using one same model to analyze different phenomena, it will be easier to see the correlation between those phenomena. The other cognitive models mentioned above are specifically designed to analyze norm emergence. Therefore, it will more difficult to see the correlation with other cognitive phenomena.

2.5.3 Mental subgrouping process

Mental subgrouping process is an inherent process in human's mind (Mahardhika et al., 2016). Due to limited cognitive ability, human cannot comprehend cognitive status (opinion, expectation, and so on) of many people at once. The emergence of norm involves interaction with many other people at once. Besides, due to the nature of the society, where there are so many members and it is impossible to interact with all members, mental subgrouping always happen in the process of norm emergence. To represent the real condition, this mental subgrouping process needs to be incorporated in the model of norm emergence. The model proposed in the current study uses mental subgrouping process as one of its important process in comprehending the cognitive status of other agents.

2.5.4 Bottom-up emergence

The term 'emergence' has been used in many norm simulations. The emergence of a norm is usually defined as the moment when the particular norm has been adopted by a certain number of people in the society (Hollander & Wu, 2011). Even though the word 'emergence' itself has the nuance of 'bottom-up mechanism', the term 'norm emergence' does not necessarily imply a bottom-up emergence as mentioned in Section 1.2.1.

In the conventional use of the term 'norm emergence', the norm is already embedded in the superior agent(s), and later spreaded and adopted by the society. In this sense, such emergence is using a top-down mechanism. In the review of norm simulation researches by Savarimuthu and Cranefiled (2011), there are only two researches that adopts bottom-up emergence. One is by Hoffmann (2003). He called the mechanism "entrepreneurship mechanism of norm emergence". Every agent in the society 'picks' an action (represented by a value from 0-100). Some agents that have a closer value to the average of the society will be able to punish other agents. In the research by Verhagen (2001), all agents have different actions and those actions have the same possibility to be the norm of the society. The agents consult and influence with each other to choose the norm. However, in his research, there are 'leader agents' whose influence is 10 times higher than other agents.

Therefore, those two researches did not the isolate the bottom-up emergence from the effect of leader / superior agents. In the current study, norm emergence is modeled by using bottom-up mechanism without any superior agents.

In Sen and Airiau's research (2007), bottom-up emergence was also used. There was no superior agent in the interaction process among the agents. However, the choices of action have been limited since the very beginning. In their research, the society needs to decide whether to drive on the left side or on the right side of the road. In our opinion, a true bottom-up emergence should allow as many possible actions as there are agents. In the current study, since the beginning the agents are allowed to have a choice of action specific to their own.

2.5.5 Motivation to conform with the norm

In other studies, motivation to conform with the norm are limited to sanction, like punishment and reward (Axelrod, 1986; Flentge, Polani, & Uthmann, 2001; López, Luck, & d'Inverno, 2002) or reputation (Castelfranchi et al., 1998; Hales, 2002). A novel approach was done by using the internalization as the motivation (Andrighetto et al., 2010). In their research, an agent will conform with a norm only when they have internalized the norm. In the current study, a new approach is proposed. The motivation of the agent's action is represented by a trade-off between utilitarian motive, and a motive to conform with the majority. This motivation is explained further in Section 3.3.

Chapter III
APPROACH AND METHOD

3.1 Model of Society

According to Bicchieri's definition, a norm is a specific behavioral rule in a given specific situation or context (Cristina Bicchieri, 2006). In this section, the situation or context of the norm being modeled in this study will be discussed.

In representing the deliberation process about agent's intention and expectations, a model that contains conflict among them is needed. Besides, the model should also be able to let every agent has his/her own choice of action, not limited to just a few options. In principle, the maximum number of possible actions (thus possible norm) is the number of agents in that society.

In this study, The Tragedy of the Commons (TOC) is used as the problem to be solved by a society of agents (Hardin, 2009). There are a certain number of agents in the society, occupying a certain size of land. Each of them tries to acquire land, with the ultimate goal to gain profit from the land they acquire. The problem that needs to be solved in the TOC game is about how to distribute the resources to maximize the profit of all inhabitants, while avoiding resource quality depletion due to overconsumption. The agents' decision (the land size that they want to acquire in an iteration) is the function of their own profit calculation (intention), and also the intention of other agents.

Unlike other popular game theory used for simulating norm such as Prisoner's Dilemma, TOC offers many possible actions, not just a few (such as cooperate or defect). A single type of action in TOC is represented by a single value of the acquired land. If there are five agents acquiring different land sizes, it is said that there are five possible actions that has the possibility to become the norm in the society. This can better reflect the real world situation where people can have many alternatives in deciding their action. The norm that is expected to emerge in the end is a subset of those actions.

The agents in this society are connected to each other using an observation network. Each agent is connected to a certain number of partners (less than the size of the population) in a unidirectional way. It means that if Agent A can observe Agent B, it does not necessarily mean that B can also observe A.

3.2 Model of Agents

The starting point of the norm emergence is the individual actions. To avoid confusion between this individual actions and the actions based on norms, the discussion about '*action before norm emerges*' is referred to as *intention* of the action. Individual agent can have independent *intention* and after affected by the norm emergence, the actual *action* can be different from the *intention*. In real life, we can see this phenomenon in many situations. For example, when we see a dying person on a busy street, we may have the *intention* to help him or her. However, after watching that nobody helps him or her, we might think that not helping this person is the right thing to do, so finally our *action* is to ignore that person. This example is called 'pluralistic ignorance' or 'bystander effect' (Darley & Latane, 1968).

Another important element in norm emergence is how the agents deliberate about their own action and their partners' actions. As mentioned previously, according to Bicchieri (2006) there are two types of expectation that need to be fulfilled in order that a person will recognize that a norm exists. The first is empirical expectation which says that there should be a large number of people who conform to that norm. The second is normative expectation which says that there should be a large number of people that expect the person to conform to that norm.

By comparing the intention, empirical expectation, and normative expectation, agent will then decide the action that they will take. This process is modeled by using the mutual belief model.

The ultimate goal of every agent is to increase his/her land size to get maximum profit. It is also assumed that every agent will always conform to a norm if he/she perceives that a possible norm exists. This assumption is based on Cialdini and Goldstein's argument that human has an inherent tendency to conform with others (Cialdini & Goldstein, 2004).

Agents also know that the land is limited, and when reaching the limit, the quality of the land will decrease. The decrease of the land quality will reduce the profit that the agents get. However, they do not know the total occupancy of the land.

In the simulation, agents update their intentions (1st layer) and beliefs (2nd and 3rd layers) by making a profit calculation and interaction with each other, respectively. The process is explained as follows:

3.2.1 The update of the 1st layer

To decide the intention, agents need to calculate their profit. The profit $P_{i,t}$ of an agent i at time t is calculated using Equation III-1. $a_{i,t}$ is land size acquired by the agent i at time t. W_t is the profit factor at time t.

$$P_{i,t} = a_{i,t}.W_t$$

Equation III-1. Agent's profit

Profit factor is determined by the land occupancy. When reaching full occupancy, the land quality will gradually decrease, which is given by Equation III-2. a_{total} in this equation is the total land available in the society.

$$W_t = \begin{cases} 1 & when \left(\frac{\sum_i a_{i,t}}{a_{total}}\right) \leq 80\% \\ 5 - 5\left(\frac{\sum_i a_{i,t}}{a_{total}}\right) & otherwise \end{cases}$$

Equation III-2. Profit factor
(as published in Mahardhika, et.al. (2017))

When planning for the next iteration, agents will consider a ratio called $R_{i,t}$, which is the ratio between the current profit $P_{i,t}$ and the maximum profit $P_{i,max}$ that the agent has gained since the first iteration (from t=0 up to the current t)

$$R_{i,t} = \frac{P_{i,t}}{P_{i,max}}$$

Equation III-3. Profit ratio

Agent's intention is implemented as the land size that the agent wants to acquire, labeled as PA. It is calculated by Equation III-4. The variable g_i is the default land increment of agent i, which indicates the personality of the agent whether it is greedy ($g_i = 3$), balanced ($g_i = 2$) or modest ($g_i = 1$).

$$PA_{i,t+1} = \begin{cases} a_{i,t} + g_i & when\ \ R_{i,t} \geq 1 \\ a_{i,t} + \left\| R_{i,t} \cdot (g_i - 1) \right\| & otherwise \end{cases}$$

Equation III-4. Agent's intention
(as published in Mahardhika, et. al. (2017))

$L1_{i,t}$ is the status of the first layer of agent i at time t. The value is equal to $PA_{i,t+1}$. The assumption behind the above equation is as follows. Since all agents want to gain more profit, as long as their profit is bigger than or equal to their previous maximum profit, they will keep adding land. When adding the land results in a lower profit than their previous maximum one, they will suspect that the land almost reaches full occupancy. Therefore, they will slow down their land acquisition. Since the size of the land represents one discrete action (and a discrete norm candidate) PA is always rounded to the nearest integer.

3.2.2 The update of the 2nd layer

The 2nd layer ($L2_{i,t}$) of an agent is updated by asking about the 1st layer of the agent's partners. $L2_{i,t}$ contains a set of pair-values (x,y) consisting land-size plans intended by the partners, where x is a land size value, and y is the number of partners that are planning to acquire x unit of land. Since some other agent will ask about the status of agent i's $L2$, it is also necessary to provide a single value representing set $L2_{i,t}$. $L2agg_{i,t}$ is the aggregate of the values in $L2_{i,t}$. The aggregation method will be explained in Section 3.4.

3.2.3 The update of the 3rd layer

Next, to update the value of the third layer, similarly agent i will ask about the partners' second layer $L2agg_{j,t}$, where j are the index of the partners. The value will be stored in $L3_{i,t}$, which also contains pair values of x and y, similar to $L2$.

In real life, even though we can observe other people's behavior, understanding other people's intention is not always possible. To represent such situation, in the simulation a certain portion of communication attempts (both in asking partner's L1 and L2) are designed to fail. When it fails, it means that when an agent asks about another agent's intention or expectation, the agent will not receive an answer. In such situation, the asker will infer the answer from the last known norm which is calculated by aggregating land size off all observable agents in the previous iteration. The aggregation method will be explained in Section 3.4.

3.2.4 Finding norm candidates

After updating the 1st, 2nd, and 3rd layer, agents will try to find the candidates of the norm. One important notion in this process is norm threshold value. In her definition, Bicchieri (Cristina Bicchieri, 2006) mentioned that for each expectation to be fulfilled, there should be large number of people that fulfilled it. The threshold number that defines the 'large number of people' is very subjective, and can be different between different norms.

In this simulation, every agent is equipped with different threshold values. Let NT_i be the norm threshold value of agent i. Each value of x in $L2$ and $L3$ will be a norm candidate for that agent, when both of the following conditions are met:

- The corresponding y value is larger or equal to NT_i
- The value x exists both in $L2$ and $L3$

Let $C_{i,t}$ be the set of norm candidate values, thus:

$$C_{i,t} = \{x \mid (x,y) \in L2_{i,t} \land (x,y) \in L3_{i,t} \land y \geq NT_i\}$$

Equation III-5. Norm candidate set
(as published in Mahardhika, et. al. (2017))

The values inside this set will be refined further using different strategies. This will be mentioned in Section 3.4. Finally, using the set $C_{i,t}$ and also the value of $L1_{i,t}$ agent i will decide $a_{i,t+1}$, by using the following rule. If $C_{i,t}$ is empty, $a_{i,t+1} = L1_{i,t}$. Otherwise, it will choose a value from $C_{i,t}$ that is the closest to $L1_{i,t}$, either larger or smaller. The flow of the agents' decision making is shown in Figure III-1.

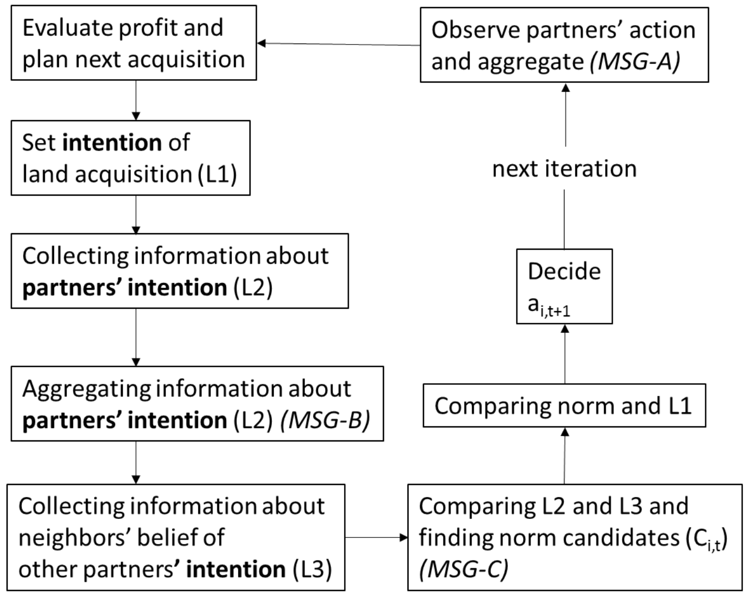

Figure III-1. Agent's decision making process (as published in Mahardhika, et. al. (2017))

In the simulation, a norm is represented not as a single metric, but as the agents' perception towards it. In the above formulation, for an agent *i*, any element of $C_{i,t}$ is a possible norm. Norm and individual action are influencing each other continuously until they reach a stable condition, as shown in Figure III-2. The perceived norm will influence individual action, and individual action will influence other agent's perceived norm, which in turn will affect the agent's perceived norm in the next iteration, and so on.

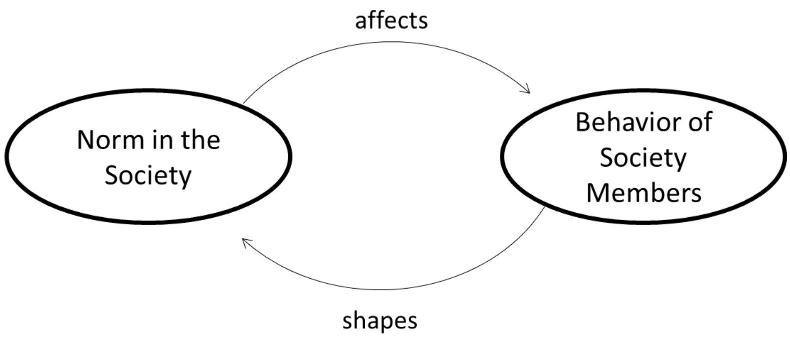

Figure III-2. Feedback loop of norm emergence

3.3 Model of Norm

As explained in Section 2.3, norms can be viewed from two perspectives. The first is from the objective perspective. This is the perspective used by most of the research about norm simulation. For example, in Savarimuthu, Purvis, Purvis, and Cranefield (2009), the norm is ‘not to litter’. There are two categories of agents: those who obey the norm (do not litter) and those who does not obey (do litter). There is only one norm in the society and it is the same for all agents. This modeling fails to explain that different agent might have different understanding of ‘what the norm is’, not just whether they obey a norm or not. Two agents might think that they are obeying a norm, but their action can still be different if they have different perception of the norm.

In this research, norm is viewed from the perspective of each agent’s mind. This is called the subjective perspective. In the end of the simulation, the emergence of the norm is not necessarily a uniform action among the agents. When agents think that they are following a norm but the perceived norms are different, the final action may be different.

Using such a perspective, emergence of norms is not modeled based on the number of agents that follow a certain norm, but based on the convergence of the agents’ actions. Higher convergence of agents’ action indicates that the agents have a similar perception of what the norm in the society is.

Another important feature of norm model in this research is that the agents are not always sure about the perceived norm. As explained in the previous section, before deciding the action agents will compare its own intention with the content of norm candidates set. The number of values in the set is usually larger than one. This represents the uncertainty that the agent face when deciding which one is the norm.

The agent then will choose one value from the set that is closest to its own intention. This feature represents the agents’ effort to conform with the society, but at the same time want to follow his own intention. This trade-off tendency conforms with Bicchieri’s (2010) argument that norm should be a mixed motive game. This means that there are utilitarian motive (maximizing his own profit) and also the motive to conform with others.

3.4 Variation of Mental Subgrouping Strategy

In the decision making process (as shown in Figure III-1), there are several steps where the agents are required to consider information about or from their partners. As mentioned previously, it is assumed that agents cannot consider the action of all members of society, but instead, only a portion of it. Besides, when observing the observable partners, they need to aggregate the information into one value. Therefore, mental subgrouping strategy is needed.

There are three steps where the agents need to do mental subgrouping, as shown in Table III-1.

In the step marked as MSG-A in Figure III-1, the agents observes the actual action of their partners. They need to aggregate those values into a single value, which is used to infer the status of a layer when a communication fails. Let P_i be the set of partners that agent i can observe and interact with. In the beginning of each iteration, each agent i will observe the actual land size acquired by their partner j at time t-1 (denoted as $a_{j,t-1}$) for all $j \in P_i$. Let k be the size of set P_i. There are three strategies to be simulated, and also one condition where all communications will be successful. The aggregated value is called 'last known norm' and denoted as $M_{i,t-1}$.

Table III-1. Mental subgrouping strategies (as published in Mahardhika, et. al. (2017))

Step	No. of Sub-group	Strategies
(MSG-A) Aggregating observed action (used to infer unresponded query about partners' L1 / L2)	1	▪ Averaging (AVG) ▪ Most common action (MCOM) ▪ Random (RND) ▪ Perfect communication
(MSG-B) Aggregating information about partners' intention (own L2)	1	▪ Averaging (AVG) ▪ Most common action (MCOM) ▪ Random (RND)
(MSG-C) Finding norm candidates	Several	▪ Threshold (THRES) ▪ 3 most common actions (MAJ3) ▪ 3 quartiles (QUART) ▪ 3 random actions (RND)

In the 'Averaging' (AVG) strategy of MSG-A, the agent collects the value of partners' decision (their land size) and calculate the arithmetic mean and round it to the nearest integer, as shown in Equation III-6.

$$M_{i,t-1} = \left\| \frac{\sum_{j \in P_i} a_{j,t-1}}{k} \right\|$$

Equation III-6. AVG strategy for MSG-A

In the 'Most common action' (MCOM), the agent finds the most common value chosen by its partners (value with highest frequency). When the most common values are more than one (multiple values with a same frequency), the value is chosen randomly from those values. In 'Random' (RND), the value is chosen randomly from all values chosen by the partners.

As an example, let us assume that a particular agent *i* has 10 partners, and the value of land acquired by those partners in the previous iteration are as follows:

Table III-2. Example of partners' land size in the previous iteration

Partner no. (*j*)	1	2	3	4	5	6	7	8	9	10
Value ($a_{j,t-1}$)	4	2	6	7	9	4	9	11	7	11

In the AVG strategy, the $M_{i,t-1}$ for the above example will be 7. For the MCOM strategy, since there are 4 values with the highest frequency of 2, then the $M_{i,t-1}$ will be randomly picked among those values (4, 7, 9, 11). For the RND strategy, $M_{i,t-1}$ will be randomly picked among all values (2, 4, 4, 6, 7, 7, 9, 9, 11, 11).

The 'PERFECT' case is not a strategy. In the simulations with this case, communication is assumed to be always successful so the agents do not need to make any inference.

When other agents make a query about an agent's *L2*, the agent need to provide a single value instead of passing all the information it has about its partners' *L1*, denoted by $L2agg_{i,t}$. Therefore, it needs to perform another mental subgrouping (MSG-B). The strategies are averaging (AVG), using most common action (MCOM), and choosing random value from existing values (RND). The explanation of the strategies is similar with ones in MSG-A. Let P_i be the set of partners that agent i can observe and interact with, and $j \in P_i$. Let k be the size of set P_i. For the AVG strategy, it follows Equation III-7.

$$L2agg_{i,t} = \left\| \frac{\sum_{j \in P_i} L1_j}{k} \right\|$$

Equation III-7. AVG strategy for MSG-B

As an example, let us assume that a particular agent i has 10 partners, and the intention (*L1*) of its partners are as follows:

Table III-3. Example of partner's intention (partners' L1)

Partner no. (j)	1	2	3	4	5	6	7	8	9	10
Value ($L1_{j,t}$)	5	3	9	9	12	6	10	11	8	14

In the AVG strategy, the $L2agg_{i,t}$ for the above example is 9. For the MCOM strategy, the value is 9 since it has the highest frequency of 2. For the RND strategy, $L2agg_{i,t}$ is randomly picked among all values (3, 5, 6, 8, 9, 9, 10, 11, 12, 14).

As mentioned previously, agents use a threshold to decide the norm candidate (MSG-C). Besides the threshold, agents can also add several other strategies to reduce the number of the norm candidates. They can choose three most common values (MAJ3), the three quartiles of the candidate values (QUART), or three random values from the candidate values (RAND3). In 'Threshold' (THRES), the agents do not add any additional strategy to refine the norm candidates. In the MAJ3 strategy, after using the THRES strategy, the agents pick the three most common values from the candidate set. If there are multiple values with the same frequency, all of them will be chosen.

In the QUART strategy, after using the THRES strategy, the agents put the values in sequence, and choose the 25%, 50%, and 75% quartile values from them. In the RAND3 strategy, the agents choose three random values after using the THRES strategy.

As an example, let us assume that a particular agent *i* has 30 partners, and it has a norm threshold of 3. Table III-4 shows the content of *i*'s *L2* (collection of *i*'s partners' *L1*), and Table III-5 shows the content of *i*'s *L3* (collection of *i*'s partners' *L2agg*). In both table, the first row shows the value (in land unit), the second row shows the respective frequency of those values. The total of the frequency is 30, equal to the number of partners. The columns that are shadowed are those with the frequency of less than or equal to the threshold.

Table III-4. Example of the content of L2

Value	5	6	7	8	9	10	11
Frequency	4	6	2	4	7	6	1

Table III-5. Example of the content of L3

Value	5	6	7	8	9	10	11
Frequency	4	6	6	4	4	3	3

Agent *i* decides the norm candidate set by looking at the content of *L2* and *L3*. The values that exceed the threshold in both layers will be the element of $C_{i,t}$. In the above example, $C_{i,t} = \{5,6,8,9\}$. In the THRES strategy, this candidate will be used as it is.

In MAJ3 strategy, this set will be refined further by taking only 3 most common values. The frequencies of those values are calculated by rounding the average frequency of each values in both layers. Therefore, for the above set ($C_{i,t} = \{5,6,8,9\}$), the frequencies are 4, 6, 4, and 6 respectively. There are only 2 frequencies here (4 and 6) so for the AVG strategy, the set will still be $C_{i,t} = \{5,6,8,9\}$.

For the QUART strategy, it is necessary to put all the values in order as shown below, in which each values are repeated according to the new frequency calculated above:

5 5 5 5 6 6 6 6 6 6 8 8 8 8 9 9 9 9 9 9

The first quartile is 6. The second quartile (median) is 8, The third quartile is 9. Therefore, for the QUART strategy $C_{i,t} = \{6,8,9\}$

In the RAND3 strategy, 3 values will randomly be picked from the set from THRES strategy $C_{i,t}$ = {5,6,8,9}, for example $C_{i,t}$ = {5,6,9}.

The strategies mentioned in MSG-A, MSG-B, or MSG-C are by no means exhaustive. It is unknown how mental subgrouping is done in a person's mind. However, it is suspected that mental subgrouping is influenced by perceived similarity of one's partners, either in intention, characteristics, ideas, and so on. In this research, the agents' cognition is represented by their intention and expectation. Thus, similarity in them among one's partners is suspected to be the trigger of mental subgrouping. To represent this, average and majority rules are used. Another possibility is by centrality or distribution of the intention, characteristics, ideas, and so on. This is represented by using the three quartiles as mental subgroups. Random rules are chosen to accommodate the possibility that sometimes mental subgrouping is randomly done.

In the simulation, the combination of those strategies are compared and the effect on the overall actions of the agents is examined. In total there are 48 combination of strategies in MSG-A, MSG-B, and MSG-C. In one simulation, all agents will decide using one same combination.

Chapter IV
SIMULATION

4.1 Initial Setup

The first step in doing the simulation is to generate the population. A population with 200 agents was generated. The number is chosen in such a way that will give insights about the emergence but only requires a reasonable computation time.

The three characteristics (greedy, balanced, and modest, with the ratio of 3:3:4), and also the initial land size (uniformly distributed, from 1-40) were assigned randomly to the agents. For each agent, a norm threshold is also decided, uniformly distributed from 3-8.

A unidirectional interaction network was generated. For each agent, 50 other agents are randomly connected to form the network. This network is fixed throughout the simulation. To represent the limited resources in the TOC game, the size of the land is 20,000 units. The number of iterations is 800 iterations.

The complete list of the strategy combination is shown on Table IV-1.

Table IV-1. Strategy combinations

ID	MSG-A	MSG-B	MSG-C	ID	MSG-A	MSG-B	MSG-C
1	AVG	AVG	THRES	25	RND	AVG	THRES
2	AVG	AVG	MAJ3	26	RND	AVG	MAJ3
3	AVG	AVG	QUART	27	RND	AVG	QUART
4	AVG	AVG	RAND3	28	RND	AVG	RAND3
5	AVG	MCOM	THRES	29	RND	MCOM	THRES
6	AVG	MCOM	MAJ3	30	RND	MCOM	MAJ3
7	AVG	MCOM	QUART	31	RND	MCOM	QUART
8	AVG	MCOM	RAND3	32	RND	MCOM	RAND3
9	AVG	RND	THRES	33	RND	RND	THRES
10	AVG	RND	MAJ3	34	RND	RND	MAJ3
11	AVG	RND	QUART	35	RND	RND	QUART
12	AVG	RND	RAND3	36	RND	RND	RAND3
13	MCOM	AVG	THRES	37	PERFECT	AVG	THRES
14	MCOM	AVG	MAJ3	38	PERFECT	AVG	MAJ3
15	MCOM	AVG	QUART	39	PERFECT	AVG	QUART
16	MCOM	AVG	RAND3	40	PERFECT	AVG	RAND3
17	MCOM	MCOM	THRES	41	PERFECT	MCOM	THRES
18	MCOM	MCOM	MAJ3	42	PERFECT	MCOM	MAJ3
19	MCOM	MCOM	QUART	43	PERFECT	MCOM	QUART
20	MCOM	MCOM	RAND3	44	PERFECT	MCOM	RAND3
21	MCOM	RND	THRES	45	PERFECT	RND	THRES
22	MCOM	RND	MAJ3	46	PERFECT	RND	MAJ3
23	MCOM	RND	QUART	47	PERFECT	RND	QUART
24	MCOM	RND	RAND3	48	PERFECT	RND	RAND3

4.2 Result and Discussion

There are two expected effects that represents norm emergence. The first is the convergence of the agents' decision. The second is the growth of agents' decision over time. They are quantitatively represented by standard deviation of decision (land size), and average of agent's profit, respectively. The values calculated at the 800th iteration are used. Figure IV-1 shows the general overview of all the 48 strategy combinations in the default (initial setup) scenario. Different colors represent each strategy of MSG-C.

4.2.1 General overview

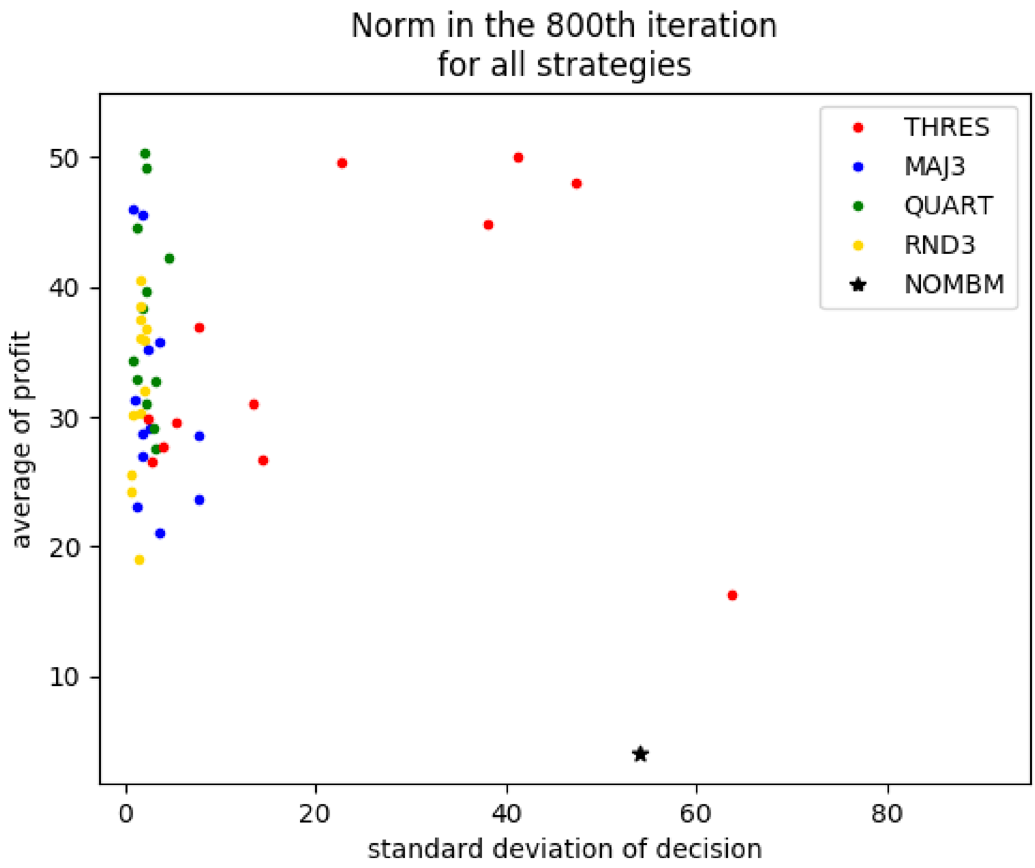

Figure IV-1. Norm emergence at the 800th iteration (MSG-C)

A good norm emergence is indicated by low standard deviation (x-axis) and high average profit (y-axis). Almost all strategies have higher average profit and lower standard deviation than the situation where the second and third layer is not used (marked by black star / NOMBM in Figure IV-1).

This simulation was done two times. In general, the norms in the 800th iteration fall only around 20-50 units of land per agent, with the final average of 33.97 (in the first trial) and 33.22 (in the second trial). This is higher than the initial average of the agents' initial land size which is 20 units of land per agent.

In the NOMBM case, agents do not take into account other agents' intention or action. When reaching the full capacity of the land, all agents decrease the rate of land acquisition, following Equation III-4. However, this individual effort is too slow, thus when they totally stop, the profit factor of the land is already very low. The high standard deviation is caused by the big gap between the acquisition rate of modest agents and greedy agents.

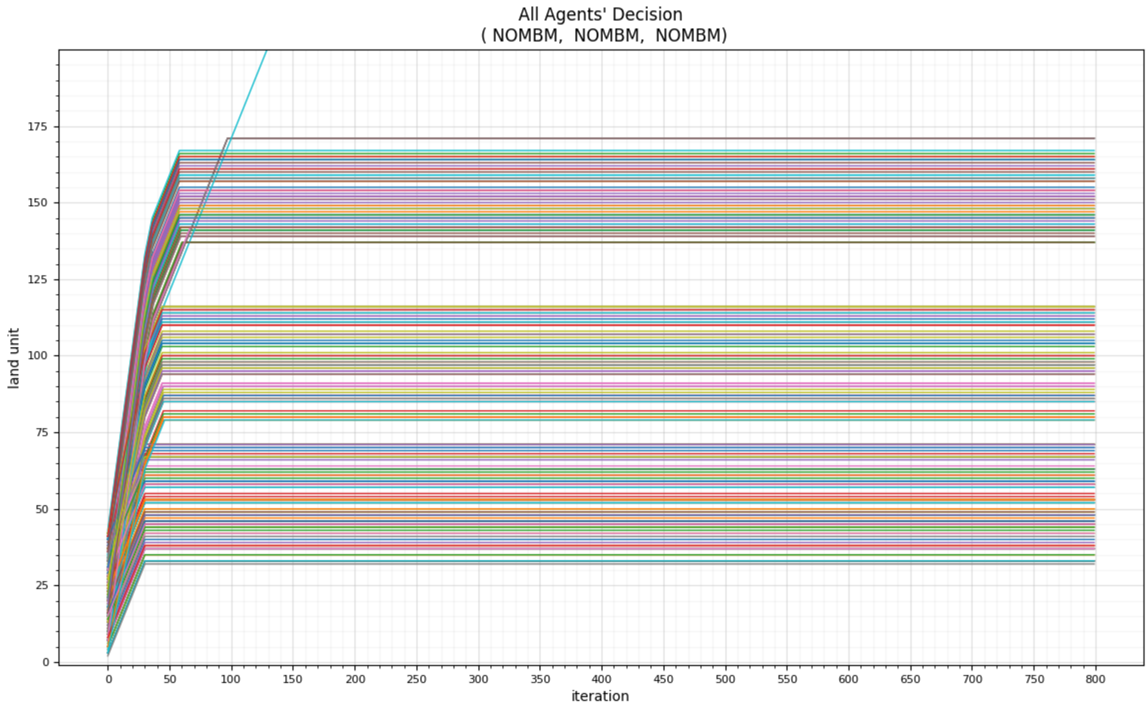

Figure IV-2. Agents' profit in the base case

Figure IV-2 shows the condition of NOMBM case. Each line in the figure represents the land acquired by each agent. The x-axis shows the iteration number. The y-axis is the land size obtained by each agent. In the beginning of the simulation, all agents increase their lands based on their characteristics. After reaching a certain point, some agents started to reach a plateau, but some other agents just slow down their acquisition rate. After around the 50th iteration the agents do not add more land. Since every agent in the end chooses different action, it can be said that there is no norm emerges in such society. The greedy agents are the latest to stop adding their land size due to their characteristics. This causes the overconsumption of the land and thus reduces its quality. In the end, the profit of all agents become very low (the black star in Figure IV-1).

Among the 48 strategy combinations, the result of three strategies are shown in Figure IV-4, Figure IV-5, and Figure IV-6. The scale on y-axis is the same with the one in Figure IV-2 (base case). These strategies were chosen to show different extreme cases. The average profit and convergence of these three strategies are shown in the red circles in Figure IV-3. The first, second, and third strategy are shown in the top-left (PERFECT-RND-QUART), top-right (MCOM-RND-THRES), and bottom-right (PERFECT-MCOM-THRES) circle respectively.

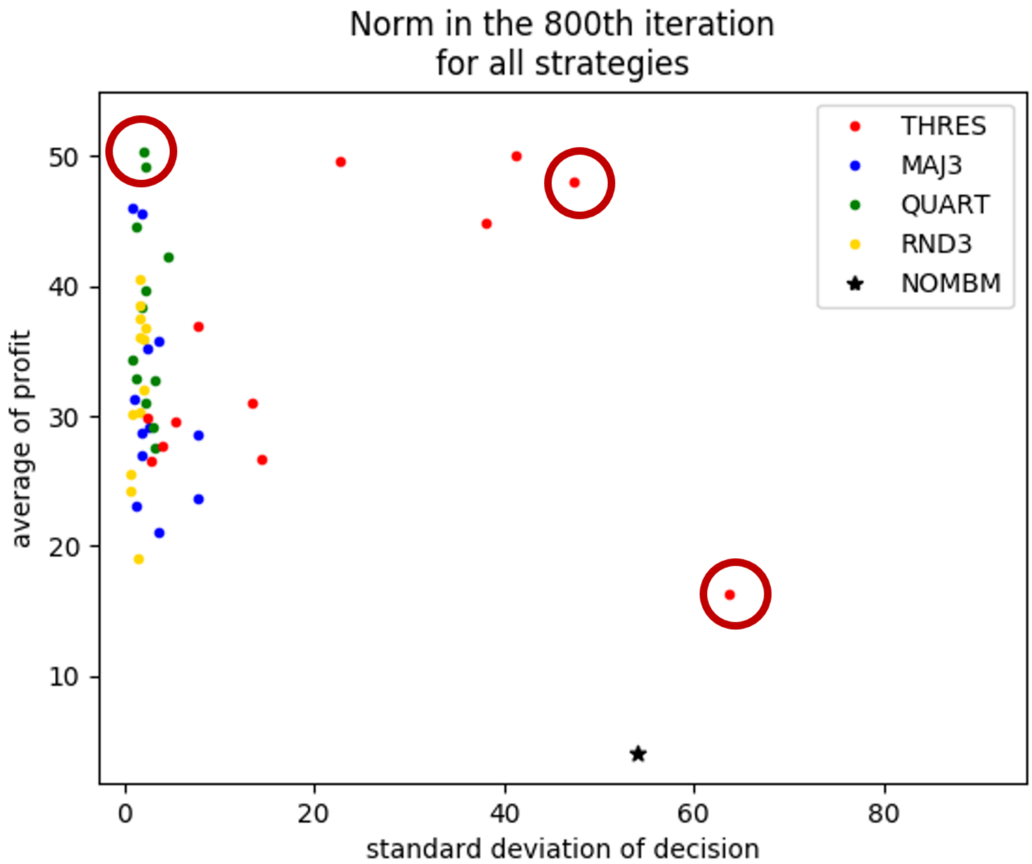

Figure IV-3. Extreme cases

Figure IV-4 shows the result of PERFECT-RND-QUART strategy. In this situation, the decisions of the agents converge in the early stage of the simulation. After that, the decision increases slowly until the end of the simulation. The average profit in the end of the simulation is 50.39. This value is the highest among the 48 combinations.

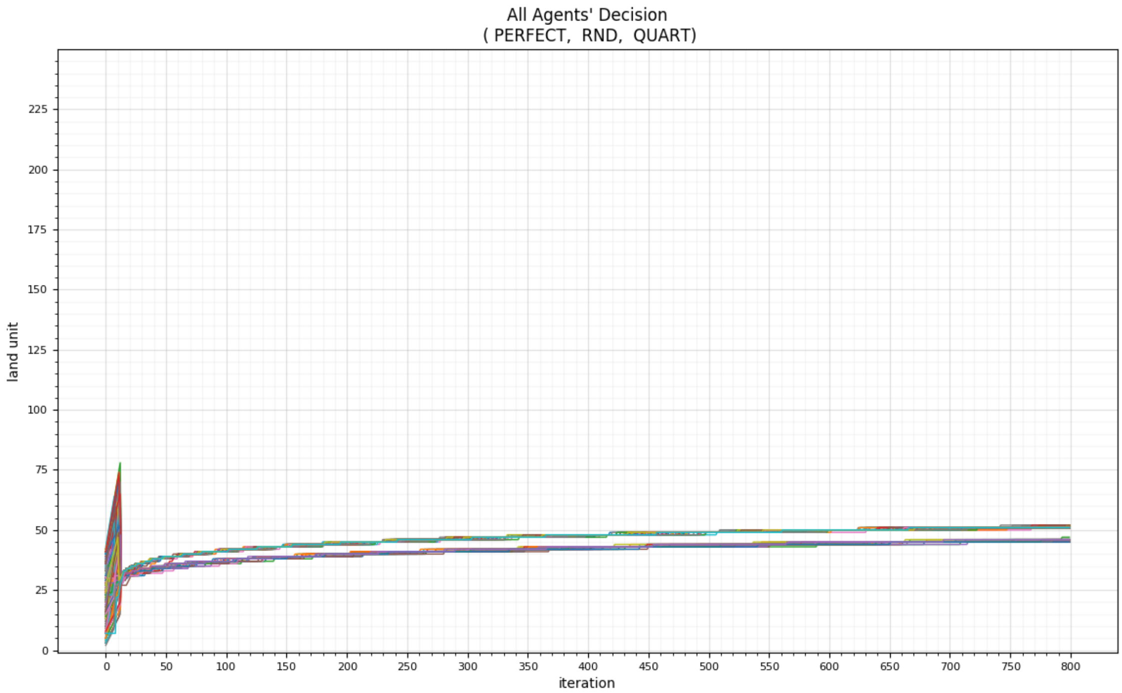

Figure IV-4. PERFECT-RND-QUART strategy

When agents consider each other intentions and expectations, they can reach a convergence of action while at the same time reach a high profit. This is caused by the decision making process. When an agent recognizes its partners' intention, it will cause the agent to adjust his decision to match with the society. All agents do the same process; thus it creates a loop that allow the whole society to indirectly coordinate their action.

Figure IV-5 shows the result of MCOM-RND-THRES strategy. In this situation, a small group of agents manage to coordinate with each other to increase their land size together. However, most of other agents stop increasing their land. Upon further investigation, it is found that the agents stop increasing their land size because their partners also do the same, not because they realize that the profit is decreasing. Overall, the high variation of agents' decision, and also the behavior of some agents that keep increasing the land create a low convergence. However, on average the profit is still high in the final iteration, which is 48.09.

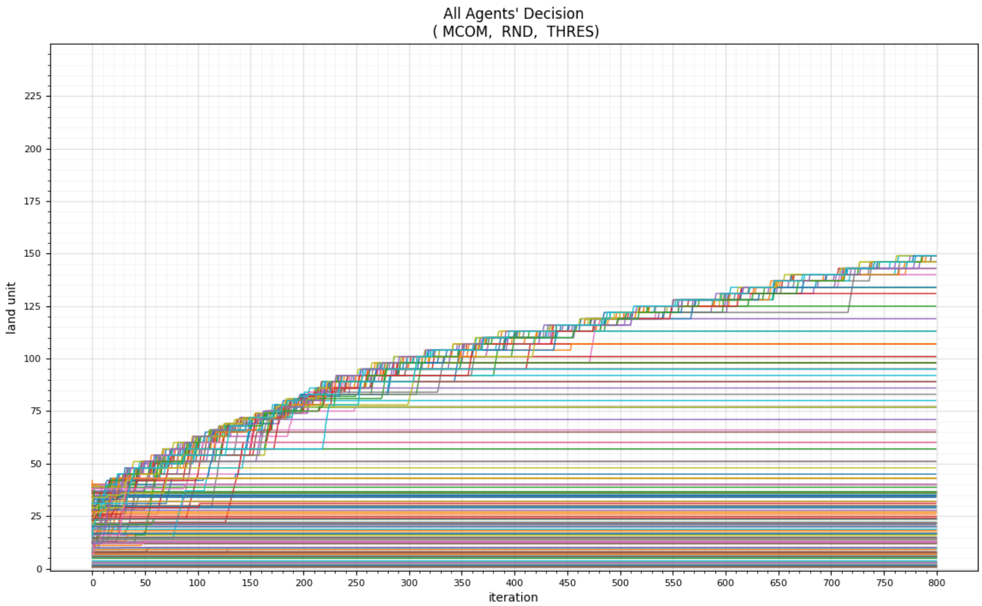

Figure IV-5. MCOM-RND-THRES strategy

Figure IV-6 shows the result of PERFECT-MCOM-THRES strategy. This case shows very low convergence in the agents' decision. Compared to the previous strategy, visually this one seems to have less variation. However, due to a very large gap between agents with large land and agents with small land, overall the convergence becomes very low. Besides, since the agents with large land were late to stop increasing the land size, the land became overconsumed. This situation creates a low land quality in the end of the simulation. The average final profit is 16.33.

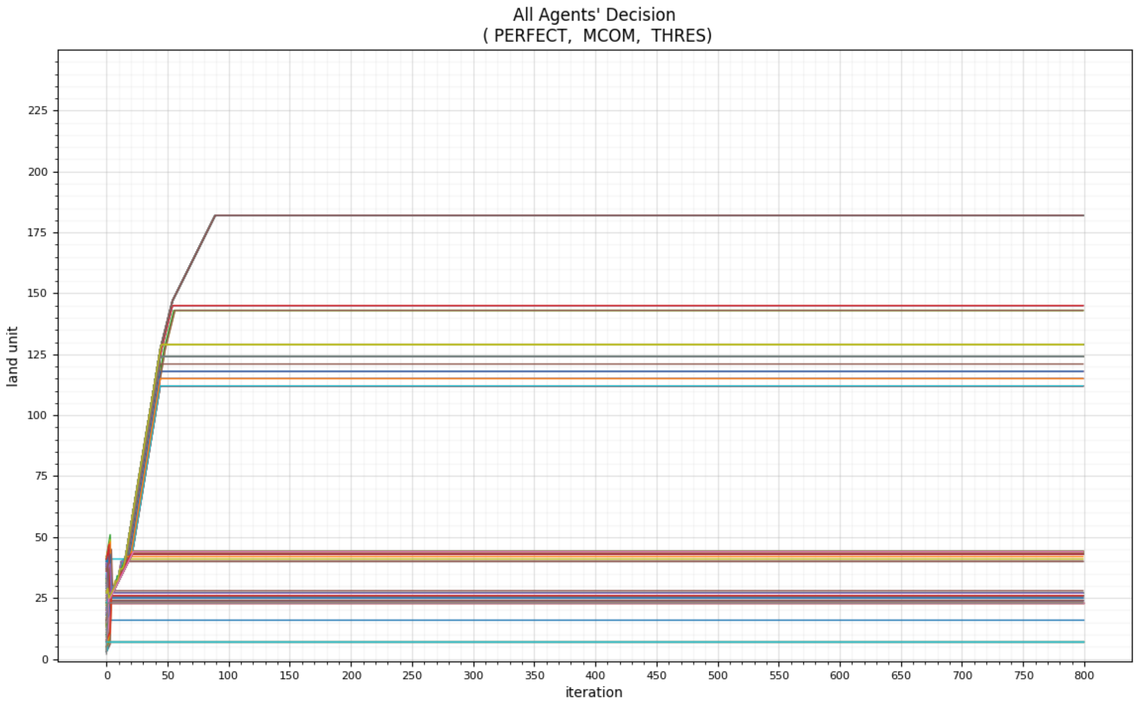

Figure IV-6. PERFECT-MCOM-THRES strategy

Figure IV-7 shows the average profit of the base case and the three cases mentioned above. As shown in the figure, the base case and PERFECT-MCOM-THRES strategy quickly reach a high profit average but later drop suddenly. The peak of profit happens due to the decreasing land profit factor once the total land occupancy reaches 80%.

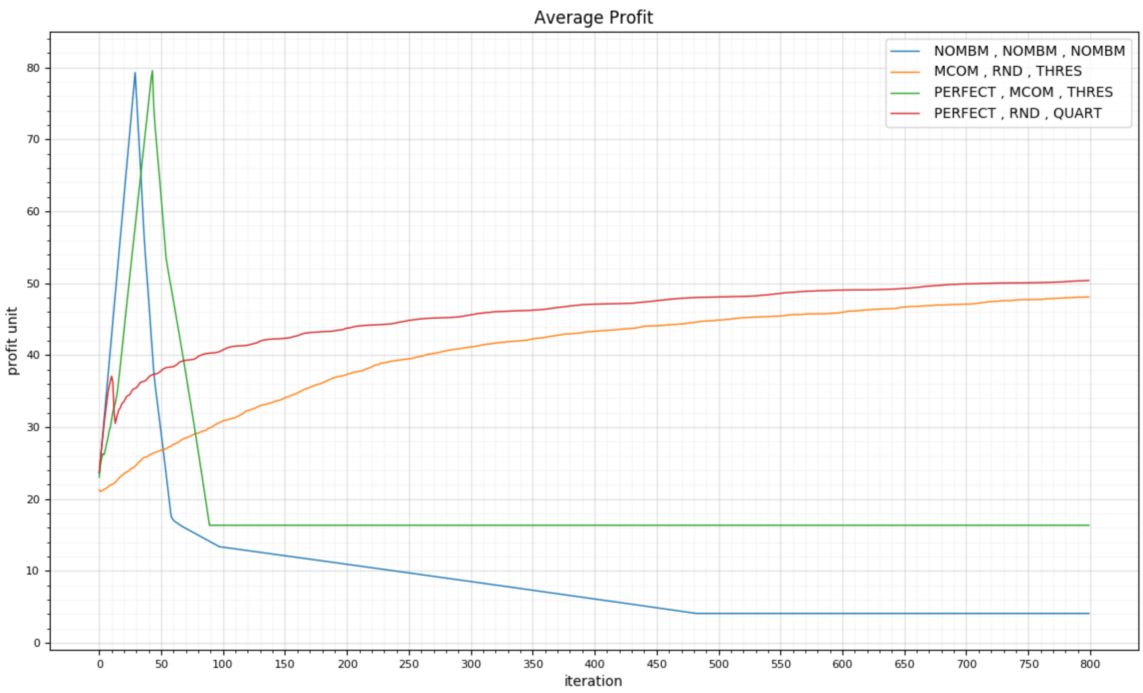

Figure IV-7. Average profit of the extreme cases

The result of all the 48 strategies in the default scenario is shown in Appendix A. Table IV-2 shows the summary of all simulations done in this study

Table IV-2. Summary of all simulations

Scenarios	Number of partners per agent	Type of network	Population composition (greedy : balanced : modest)	Strategy variation	Number of trials
Default case	50	Random, unidirectional	3:3:4	48 strategies	2
Different no. of MSG	50	Random, unidirectional	3:3:4	8 strategies	2
Small number of partners	10	Random, unidirectional	3:3:4	48 strategies	2
Large number of partners	150	Random, unidirectional	3:3:4	48 strategies	2
L3 switched off	50	Random, unidirectional	3:3:4	48 strategies	2
Greedy dominant society	50	Random, unidirectional	8:1:1	48 strategies	1
Modest dominant society	50	Random, unidirectional	1:1:8	48 strategies	1
Greedy dominant society, L3 switched off	50	Random, unidirectional	8:1:1	48 strategies	1
Modest dominant society, L3 switched off	50	Random, unidirectional	1:1:8	48 strategies	1
Small-world network	Varied, with the average of 30	Watts-Strogatz Model, bidirectional	1:1:1	48 strategies	1
Random network	Varied, with the average of 30	Erdos-Renyi Model, bidirectional	1:1:1	48 strategies	1
Scale-free network	Varied, with the average of 30	Barabasi-Albert Model, bidirectional	1:1:1	48 strategies	1

4.2.2 Sudden convergence

One important aspect in analyzing norm emergence is to see whether norm emerge suddenly in a society or through a slow but steady process. To do this, the standard deviation of agents' decision in all iteration for each strategy is plotted into a graph. Then, the graph is checked whether it has a sudden decrease or not. A sudden decrease is defined as a 2-unit or larger decrease of standard deviation in less than 10 iterations. One example of strategy with sudden decrease and one without it are shown in Figure IV-8 and Figure IV-10 respectively. Figure IV-8 is the result of AVG-RND-QUART strategy. The respective raw result is shown in Figure IV-9. Figure IV-10 is the result of RND-AVG-MAJ3 strategy. The respective raw result is shown in Figure IV-11.

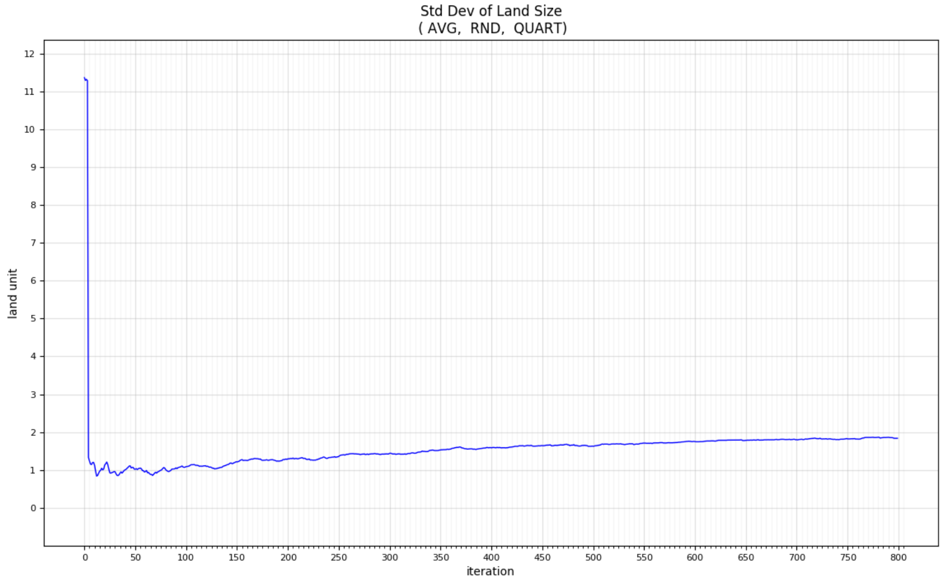

Figure IV-8. A sample case with sudden decrease

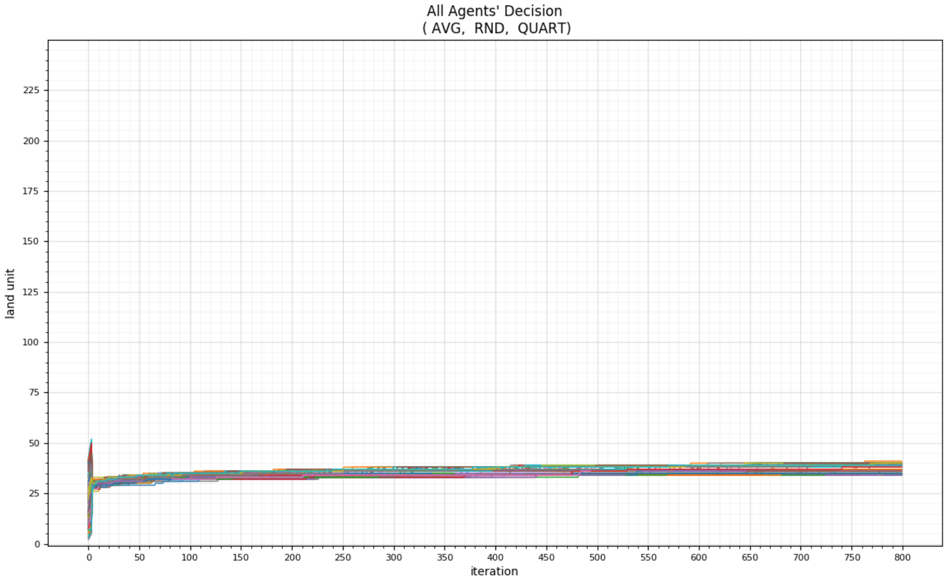

Figure IV-9. Norm Emergence of AVG-RND-QUART strategy

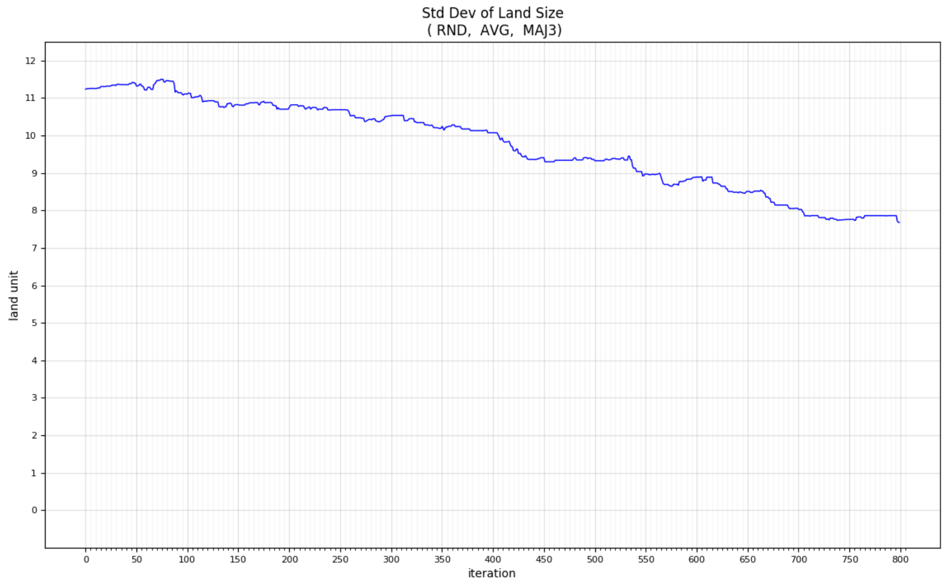

Figure IV-10. A sample case without a sudden decrease

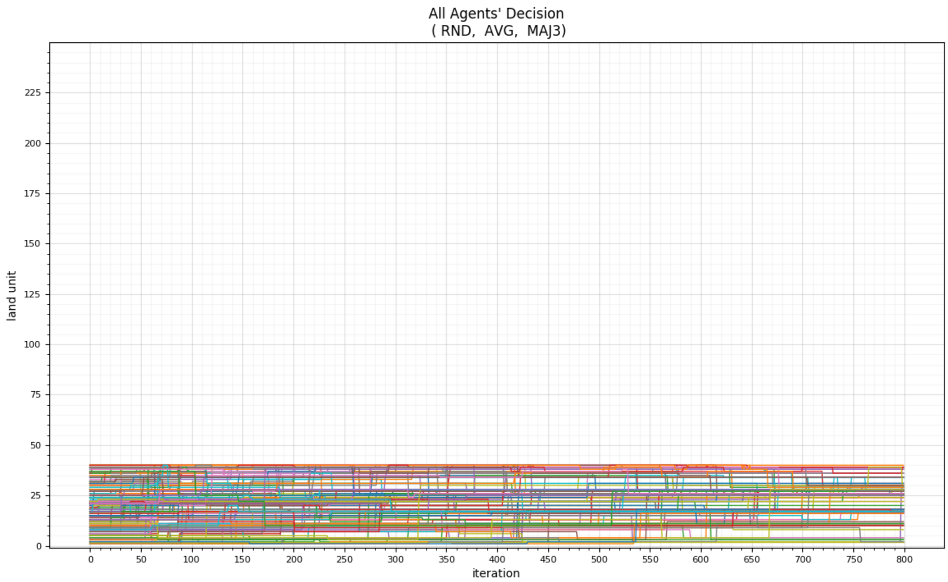

Figure IV-11. Norm emergence of RND-AVG-MAJ3 strategy

It turns out that only 5 out of 48 strategies show no sudden decrease. The list of these strategies are:

- RND-AVG-THRES
- RND-AVG-MAJ3
- RND-MCOM-MAJ3
- RND-RND-MAJ3
- RND-RND-QUART

The convergence of decision happens suddenly in most of the cases. This phenomenon is similar with the tipping concept (Schelling, 1960). The tipping concept says that when a norm shift happens, the transition tends to be sudden rather than incremental. Once a crucial threshold is crossed and a sufficient number of people made the changes, positive feedback reinforces the situation.

Similarly, in our simulation the agents shift to converged actions after there are sufficient number of people doing same action in the society. In all of the cases where a sudden decrease happens, it happens before the 60th iteration. This is a relatively early compared to the whole simulation steps. In the beginning when every agent's decision is different, they start to find out what is the norm in the society and decide based on what they find so far. After some iterations, there is a moment where the number of agents doing one same action reaches the norm threshold of most agents. This is perceived as norm, thus followed by the agents. After this major convergence, the agents will make more adjustment to try to conform with each other. In some cases (like in PERFECT-RND-QUART strategy, Figure IV-4), the agents then increase their land size together in a similar rate.

The other 5 strategies where there is no sudden decrease, all of them have the same mental subgrouping strategy for MSG-A, which is RND (random guess for inference when communication fails). It implies that accuracy in perceiving other agent's intention plays a significant role in reaching convergence in the society. If the agents do not carefully infer the intention of its partners, but instead pick a random value to update his second layer, it will be more difficult for the society to reach convergence. Careful inference in this simulation is done by either calculate the average value from previous actions, or by finding the most common actions (as explained in Table III-1, MSG-A).

4.2.3 Number of norm candidates

The strategies marked in red in Figure IV-1 are those that only use the threshold strategy for MSG-C without additional subgrouping. Most of them do not converge and have low average profit. The possible cause is the number of norm candidates that each agent has while making decision. In these strategies, the number of candidates in an iteration for an agent can reach up to 15 candidates. In other strategies, the maximum number is only three.

To see the correlation between the number of norm candidates and norm emergence, other simulations have been conducted. Simulations are conducted using the best strategy from the previous simulation that used MAJ3 strategy (the top-left blue dot in Figure IV-1, AVG-RND-MAJ3), with various number of norm candidates for MSG-C (1,3,5,7,9,11,13,15 most common values, respectively). The simulation was done twice, and the results are shown in Figure IV-12 and Figure IV-16. The raw result of 1,3, 15 common values for trials 1 and 2 are shown in Figure IV-13, Figure IV-14, Figure IV-15, Figure IV-17, Figure IV-18, Figure IV-19, respectively.

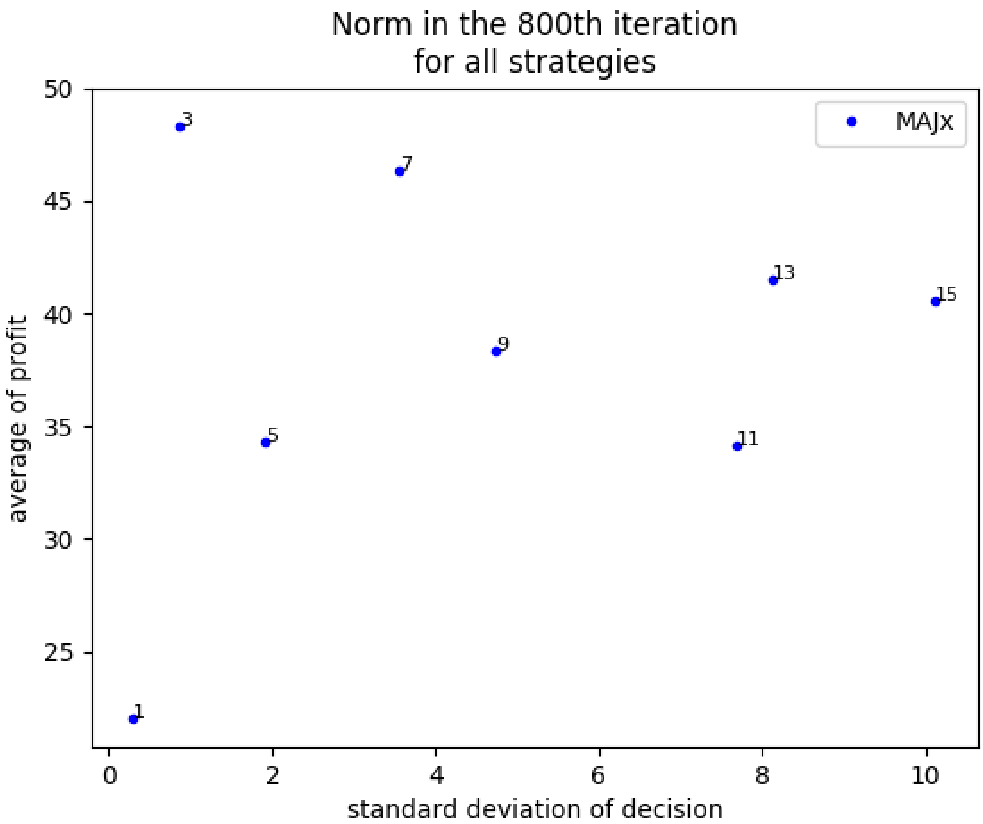

Figure IV-12. Simulations with different number of mental subgroups (trial 1) (as published in Mahardhika, et. al. (2017))

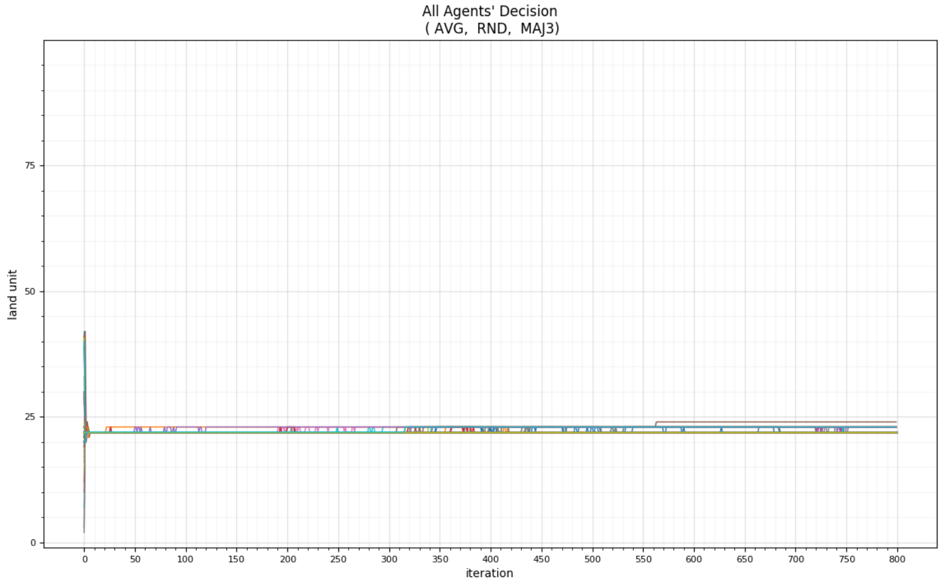

Figure IV-13. AVG-RND-MAJ3 strategy with 1 most common value (trial 1)

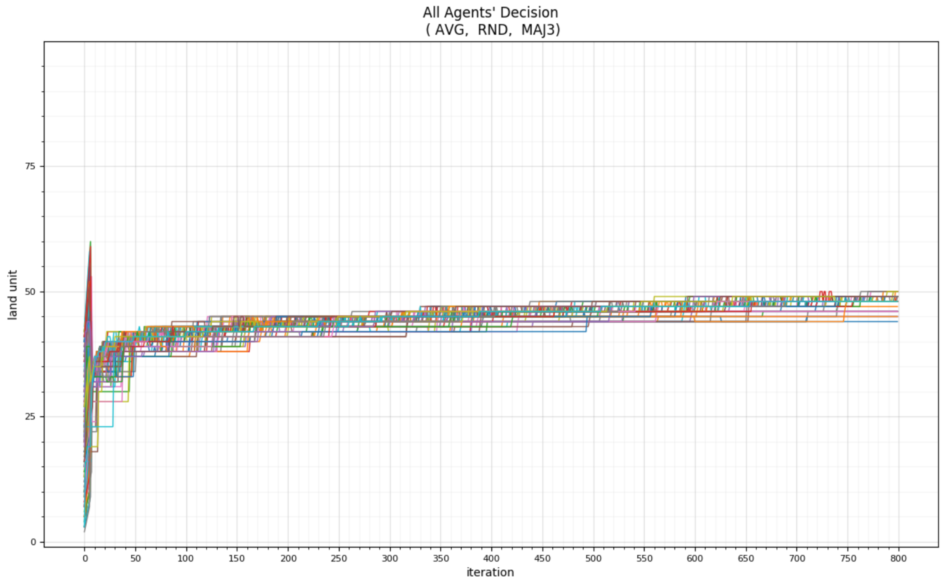

Figure IV-14. AVG-RND-MAJ3 strategy with 3 most common value (trial 1)

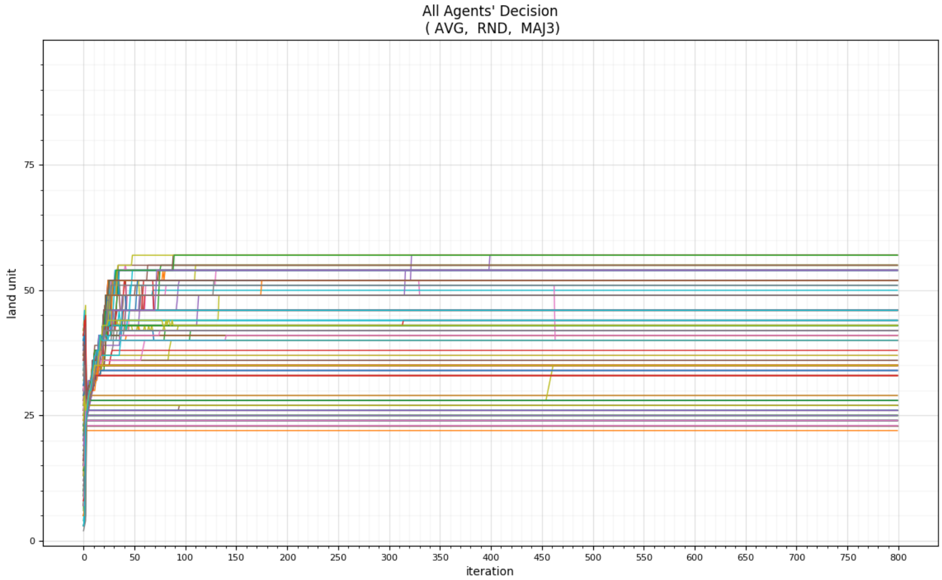

Figure IV-15. AVG-RND-MAJ3 strategy with 15 most common value (trial 1)

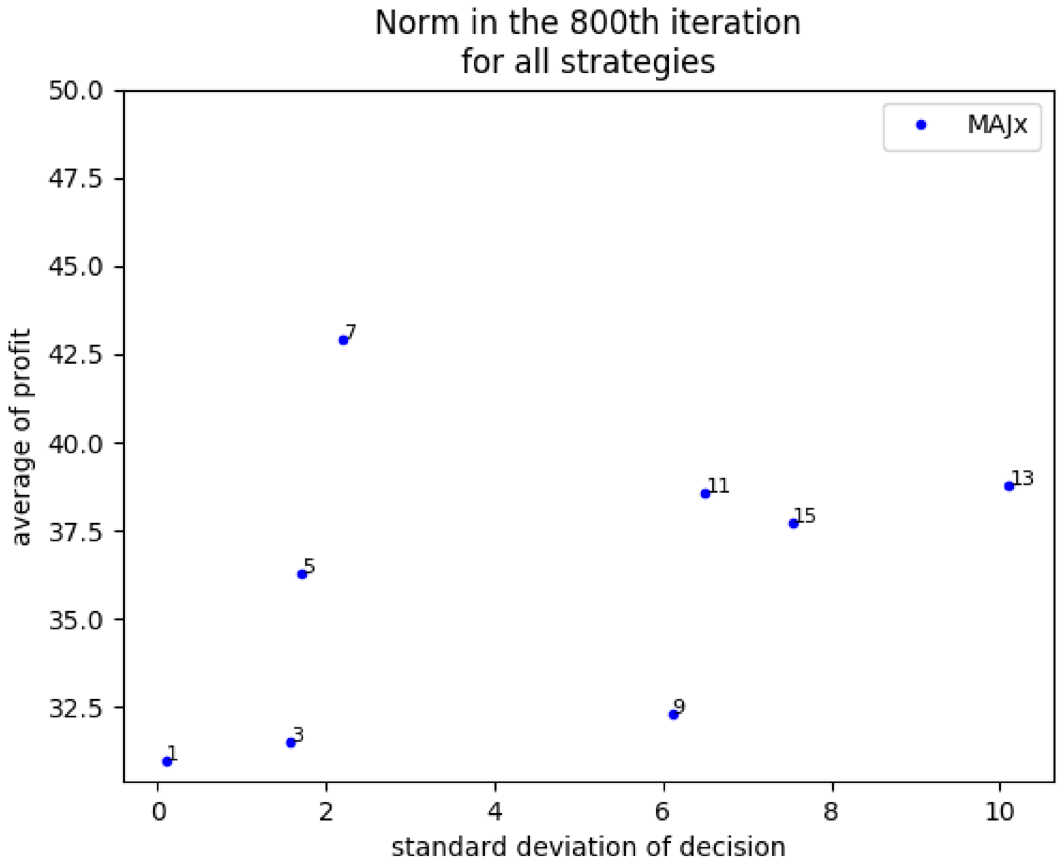

Figure IV-16. Simulations with different number of mental subgroups (trial 2)

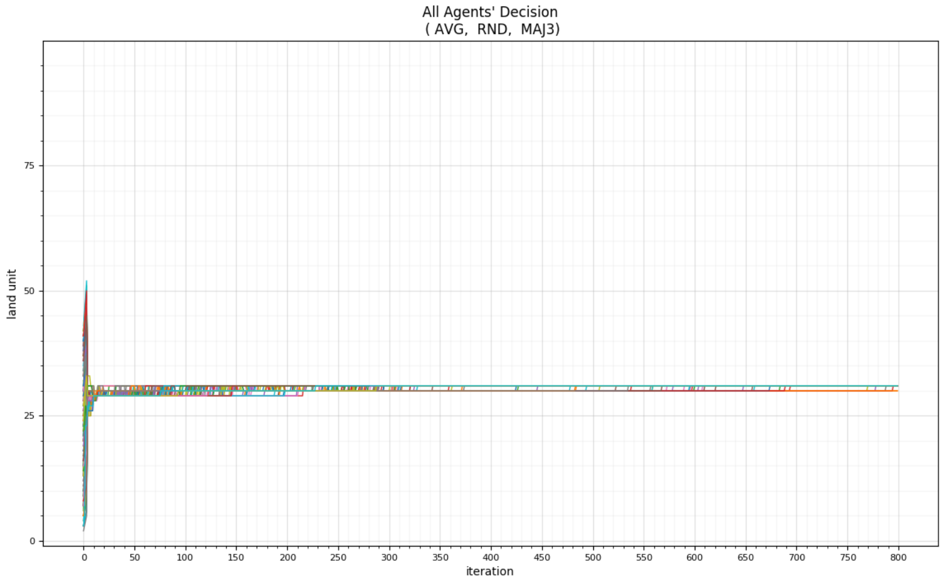

Figure IV-17. AVG-RND-MAJ3 strategy with 1 most common value (trial 2)

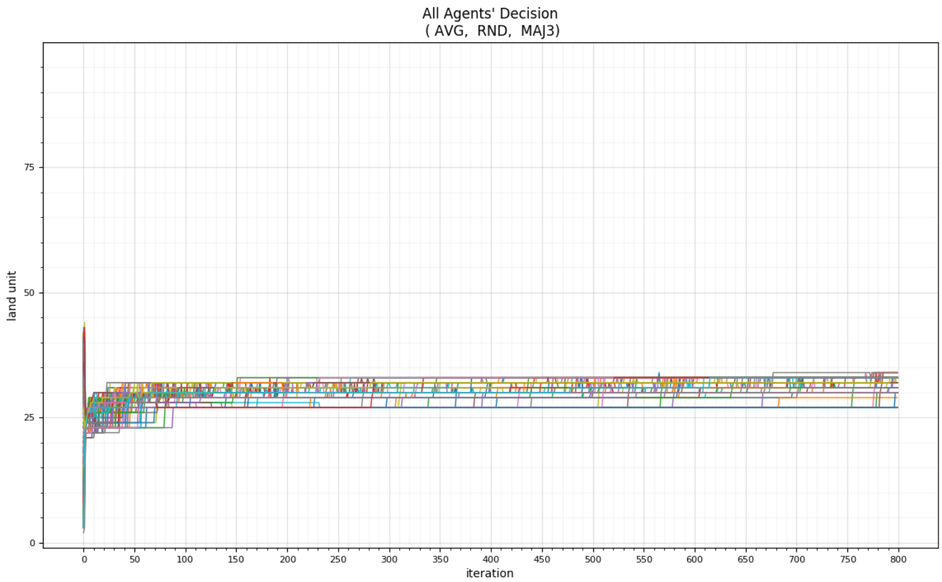

Figure IV-18. AVG-RND-MAJ3 strategy with 3 most common value (trial 2)

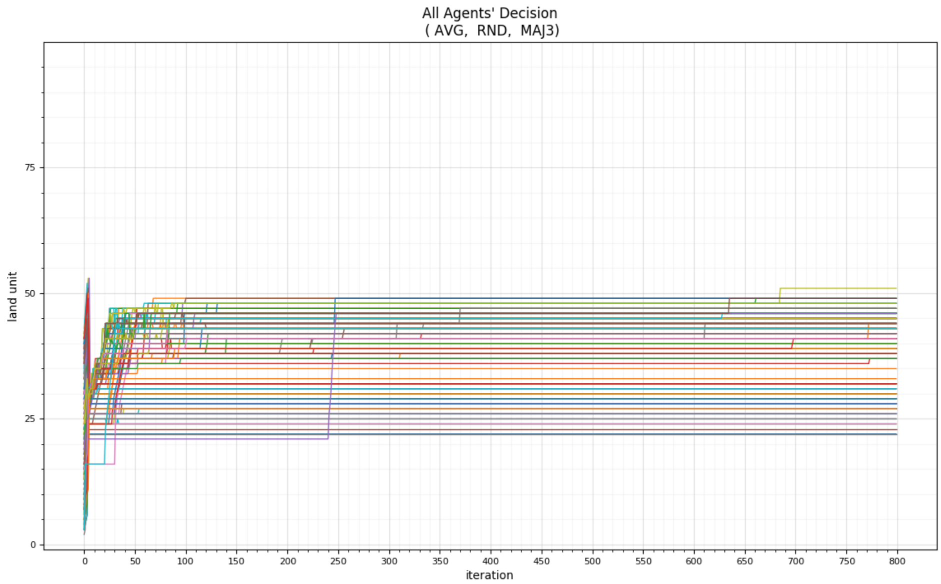

Figure IV-19. AVG-RND-MAJ3 strategy with 15 most common value (trial 2)

By using Pearson correlation coefficient, it was found that the number of norm candidates has a strong positive correlation with the convergence of the norm (r = 0.988 and r = 0.928 for trial 1 and 2 respectively). However, the average profit only has a weak or moderate positive correlation with the number of norm candidates (r = 0.308 and r = 0.554 for trial 1 and 2 respectively). This implies that number of norm candidates (number of mental subgrouping formed) affects the convergence of action in the society. However, it does not affect the average profit gained by the society.

4.2.4 Number of partners per agent

Agents cannot observe each member of the society one by one. For each agent, society is represented by the partners that are linked to it. Therefore, the partners really affect how the agent view the society. In the default scenario, each agent has 50 partners. Other scenarios were tested where the number of partners are higher (150) or lower (10).

Figure IV-20 shows the average profit and standard deviation of decision in the 800th iteration of the simulation with 10 partners per agent. The different colors represent different strategy for MSG-A. In the graph, all the dots with red color are in the same location with the base case (NOMBM, marked by the black star). The agents' behavior with the 'PERFECT' strategy is the same with when they do not consider other agent's intention or expectation. Because the agent's norm threshold stays the same, while the number of partners decreases significantly, there are not enough partners that have one same action to pass the threshold. Therefore, when making decision, agents will not find any candidate of norms in the candidate list. The decision they make will be influenced only by their own intention.

Other interesting result is that other strategies either have lower profit or lower convergence than the base case. Some of them even have both lower profit and lower convergence. Furthermore, dots with green color have negative profits.

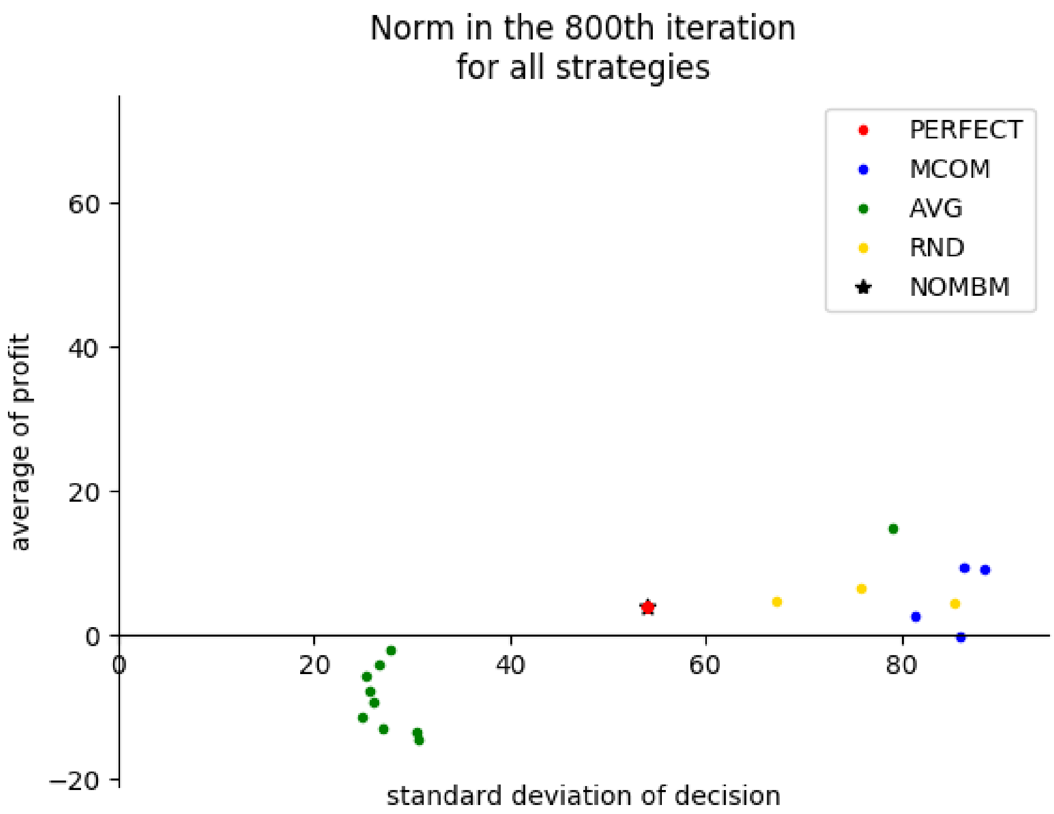

Figure IV-20. Norm emergence at the 800th iteration with 10 partners per agent (MSG-A)

Since the number of partners becomes lower while the thresholds are still the same, it becomes more difficult to find norm candidates. Besides, the individual values of partners' decision become more important. This is why the result becomes more sensitive to the strategy of *L1* inference (MSG-A), because it determines some of those values.

Figure IV-21 shows the profit of the agents using AVG-RND-RAND3 strategy with 10 partners per agent. In Figure IV-20, this strategy is the point with standard deviation of 27.86 and average profit of -1.96. The agents' decisions are very diverse. However, unlike the one in PERFECT or NOMBM strategy, we see more dynamics in the process. This indicates that the agent's decisions sometimes are still affected by their partners. Compared to the PERFECT or NOMBM where the decline of land's profit is caused by a small portion of the society (the greedy agents), in other strategies, more agents acquire more land faster, so there is a point when the land passed 100% occupancy, thus the profit factor becomes negative. This can be seen in the graph where some agents actually *decrease* their land size.

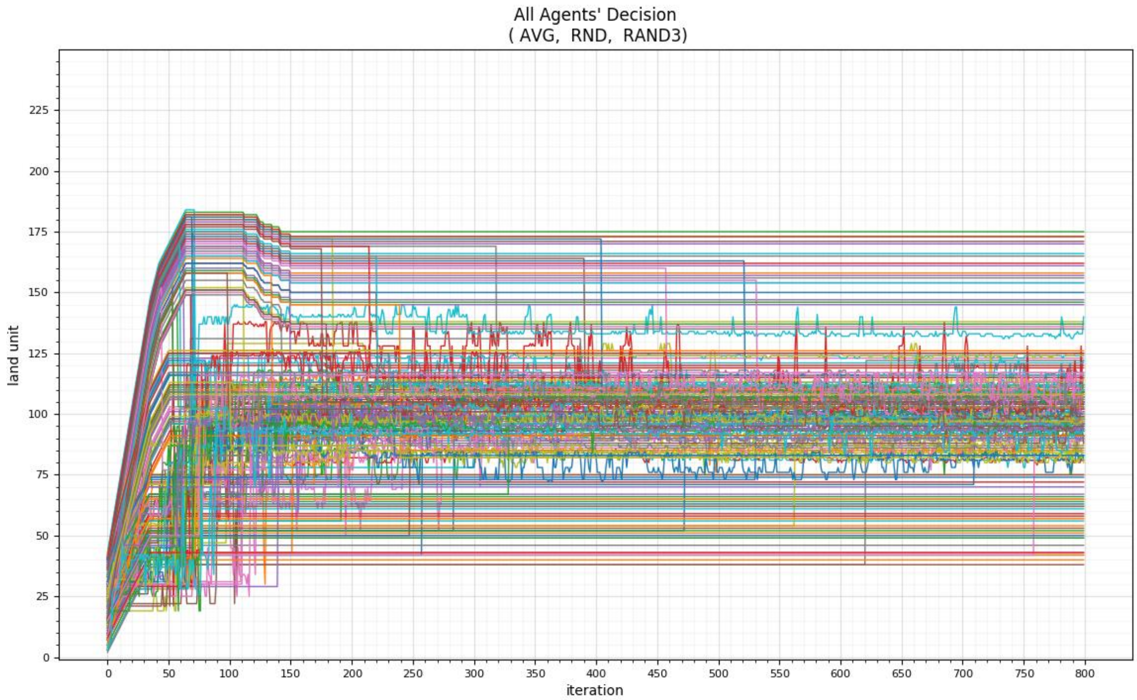

Figure IV-21. Strategy AVG-RND-RAND3 with 10 partners per agent

Figure IV-22 shows the result from the simulation with 150 partners per agent. The graph shows the strategy in MSG-A. In contrast with the 10-partner situation, all strategies in this simulation do not have negative profit. The situation is quite similar to the 50-partner case. This simulation is not sensitive to strategy in MSG-A because there are many partners relative to the norm threshold. Difference in the individual values will not significantly affect the norm candidates.

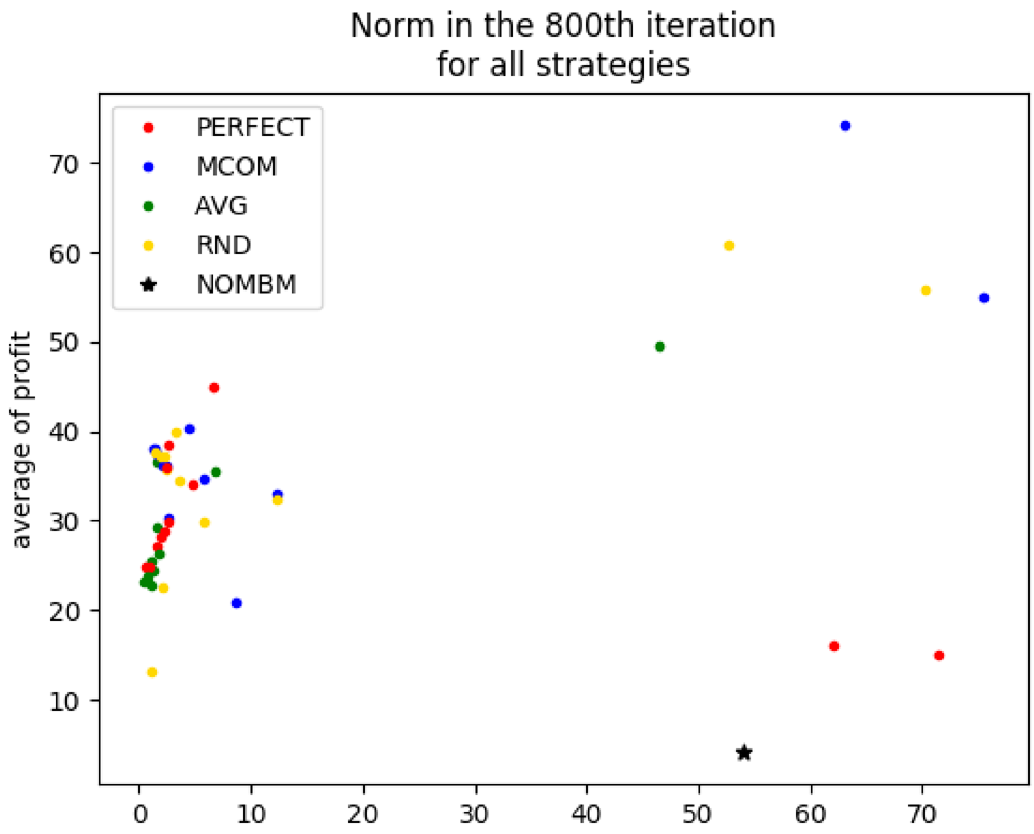

Figure IV-22. Norm emergence at the 800th iteration with 150 partners per agent (MSG-A)

However, higher number of partners causes the simulation to be more sensitive to the strategies in MSG-C, in particular the THRES strategy. This situation is shown in Figure IV-23. This graph is the same with Figure IV-22 but the colors of the dots show strategies in MSG-C. One possible explanation of why the simulation is sensitive to THRES strategy is because there are a lot more norm candidates when the agents make decision. Other strategies only allow maximum three values of norm candidates.

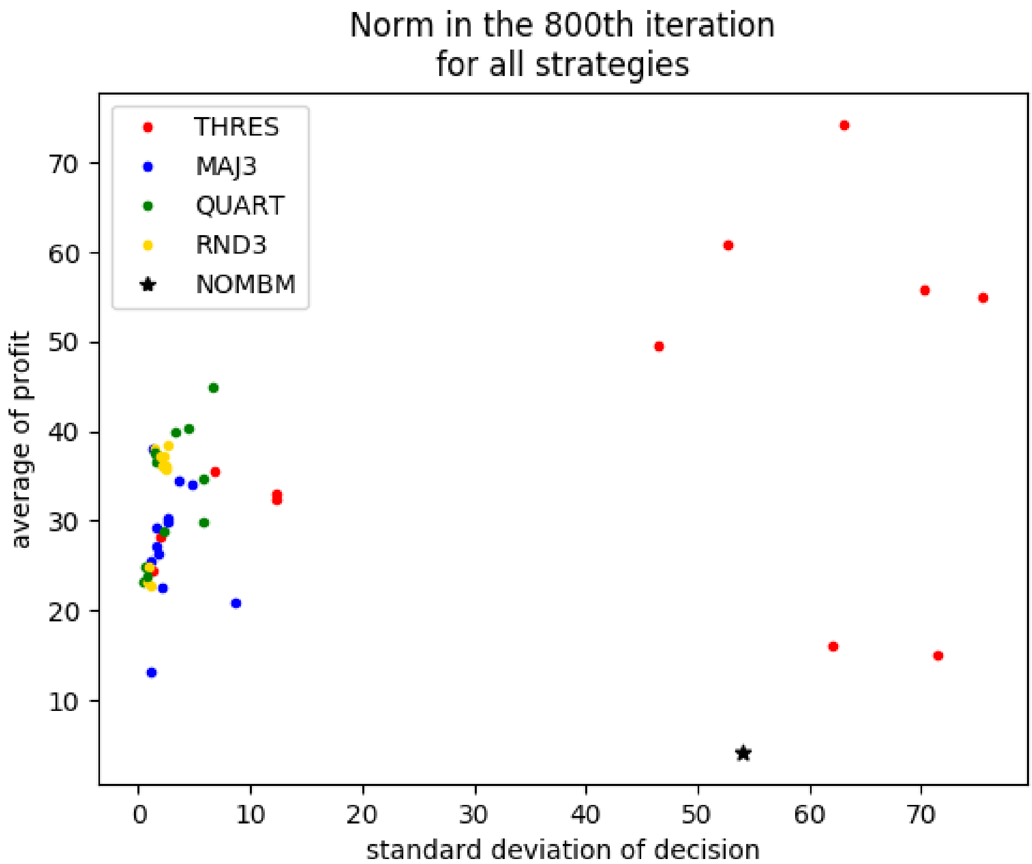

Figure IV-23. Norm emergence at the 800th iteration with 150 partners per agent (MSG-C)

Figure IV-24 shows the norm emergence process for the bottom-left case (average profit = 13.05, standard deviation of decision = 1.12, RND-AVG-MAJ3). For comparison, Figure IV-25 and Figure IV-26 show the same strategy but with 10 and 50 partners per agent, respectively.

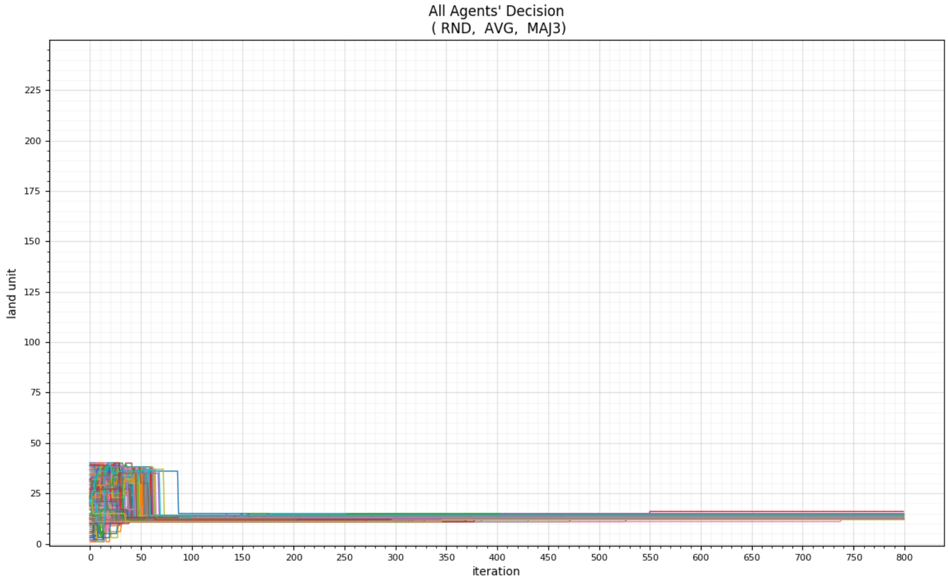

Figure IV-24. RND-AVG-MAJ3, with 150 partners per agent

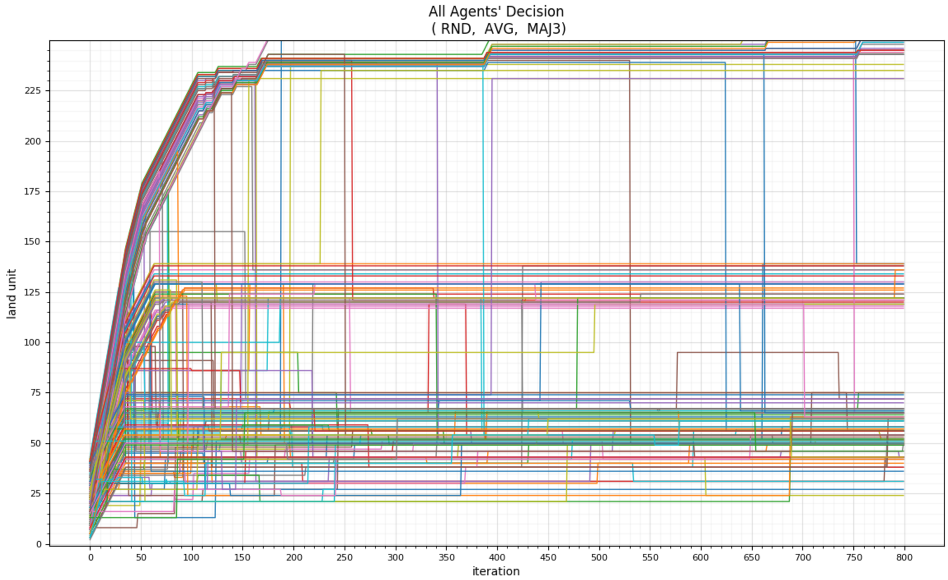

Figure IV-25. RND-AVG-MAJ3, with 10 partners per agent

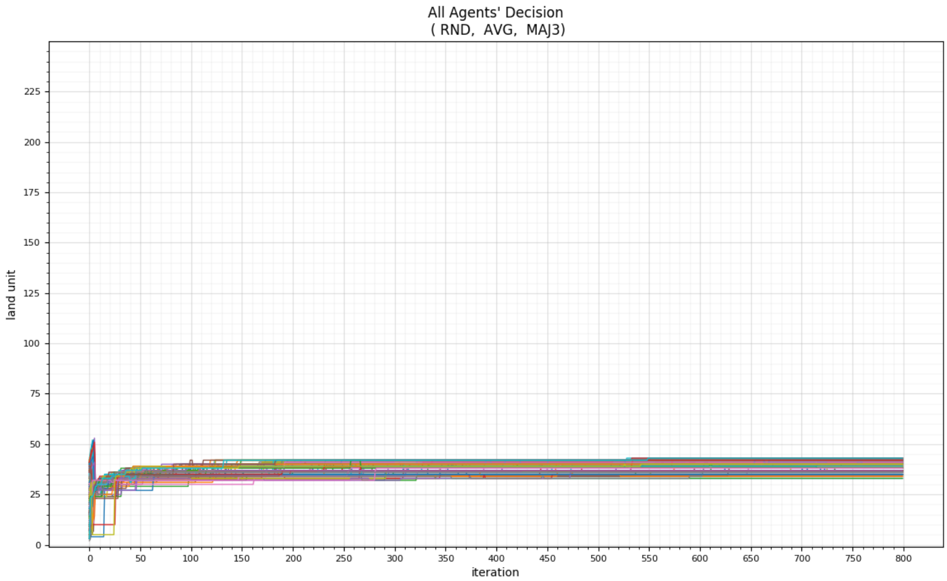

Figure IV-26.RND-AVG-MAJ3, with 50 partners per agent

In general, result from 50 partners per agent and 150 partners per agent do not show a big difference. Figure IV-27 and Figure IV-28 show average profit and standard deviation, respectively, from all strategies in the 800th iteration for 10, 50, and 150 partners per agent. The x-axis shows the ID of the strategies as explained in Table IV-1.

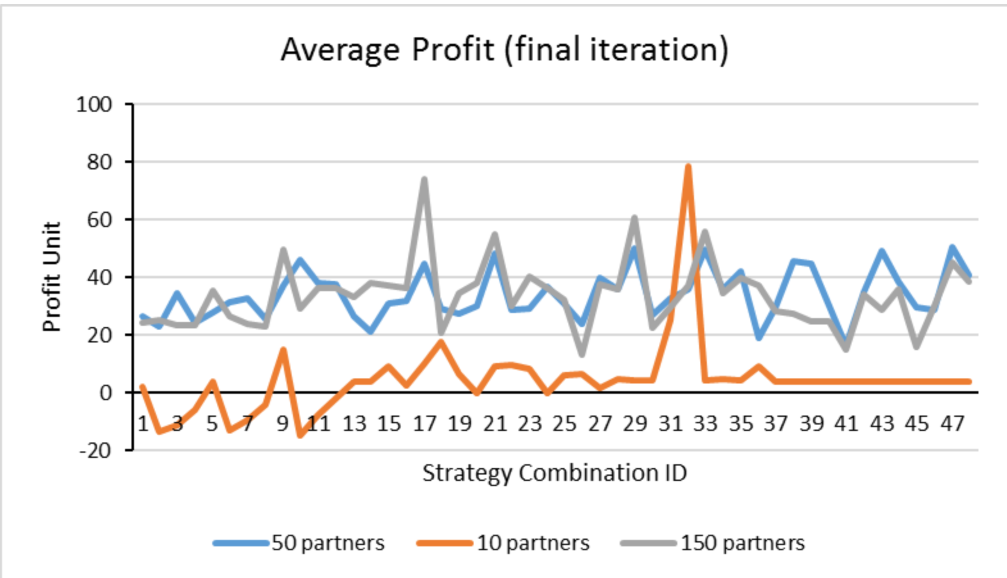

Figure IV-27. Profit comparison between different partners per agent

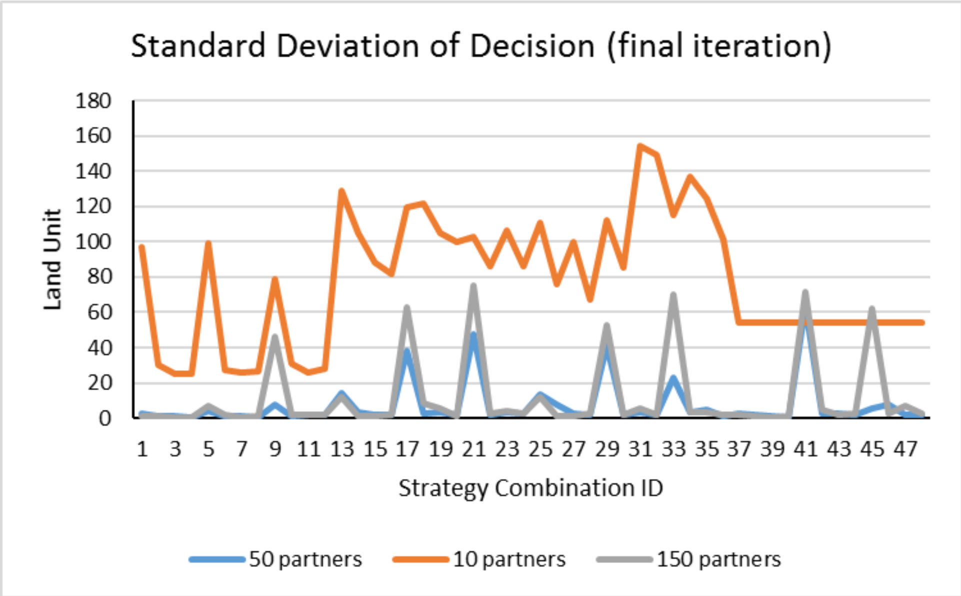

Figure IV-28. Convergence of decision between different partners per agent

From the two graphs above, the tendency is clear that 50 partners per agent and 150 partners per agent do not show a big difference. On the other hand, 10 partners per agent shows a worse performance. As mentioned above, the lack of partners makes finding norms candidate difficult. Therefore, they take actions based on their own intention.

4.2.5 The role of the third layer

In this simulation, the agents do not need to update the third layer. In this case, when deciding which values of land sizes get into the norm candidate set, the agents do not need to check whether the value exist in the third layer or not. The steps are shown in Figure IV-29.

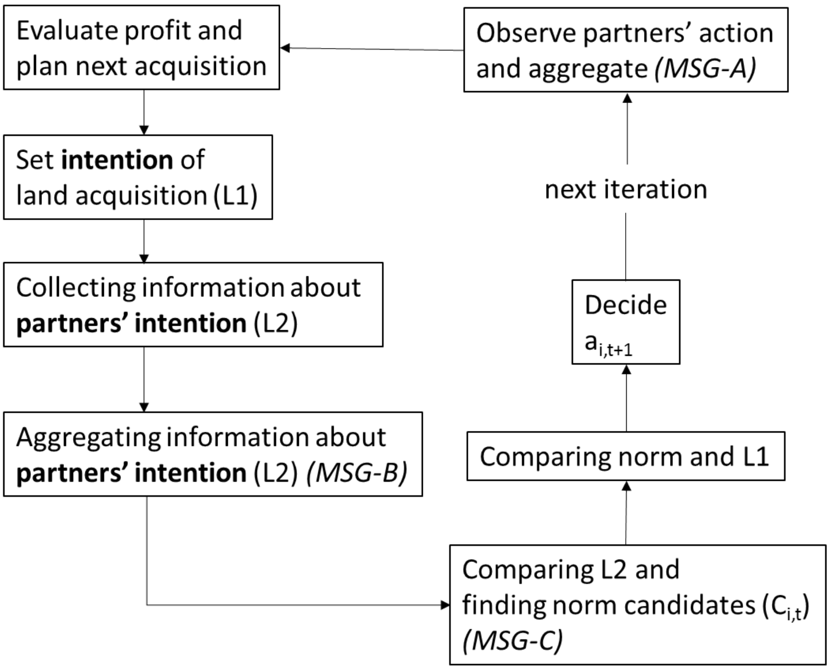

Figure IV-29. Decision making without considering the third layer

In general, this simulation gives a slightly higher profit on average than the ones using L3. The average profit in this simulation is 36.46.

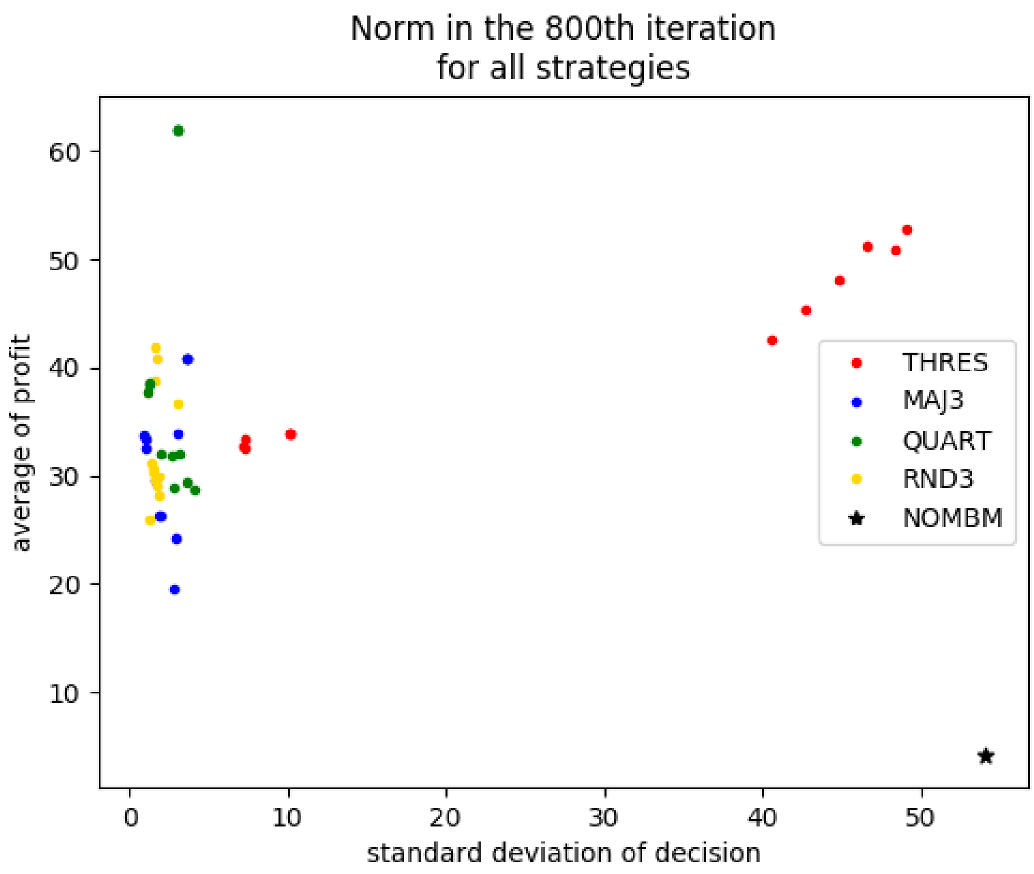

Figure IV-30. Norm emergence at the 800th iteration without L3 (MSG-C)

Figure IV-30 shows the result of the simulation without L3. One noticeable feature in this simulation result is the ones with THRES strategy that have lower convergence than others. In the case of other strategies, even though the agents do not use the third layer, the number of norm candidates is still three. Not using the third layer will result in more norm candidates since there are less requirement for a value to become a norm candidate. But if the limit of norm candidate number is three, then it will not make any difference. However, in the case of THRES strategy, the number of norm candidates is not limited. Therefore, it yields more norm candidates, that results in more diverged decision.

The best value in this simulation (the top-left side of Figure IV-30), consists of three strategies, as follows:

- PERFECT-AVG-QUART
- PERFECT-MCOM-QUART
- PERFECT-RND-QUART

The land size of PERFECT-AVG-QUART strategy is shown in Figure IV-31. The graphs of the other two strategies also have a same appearance.

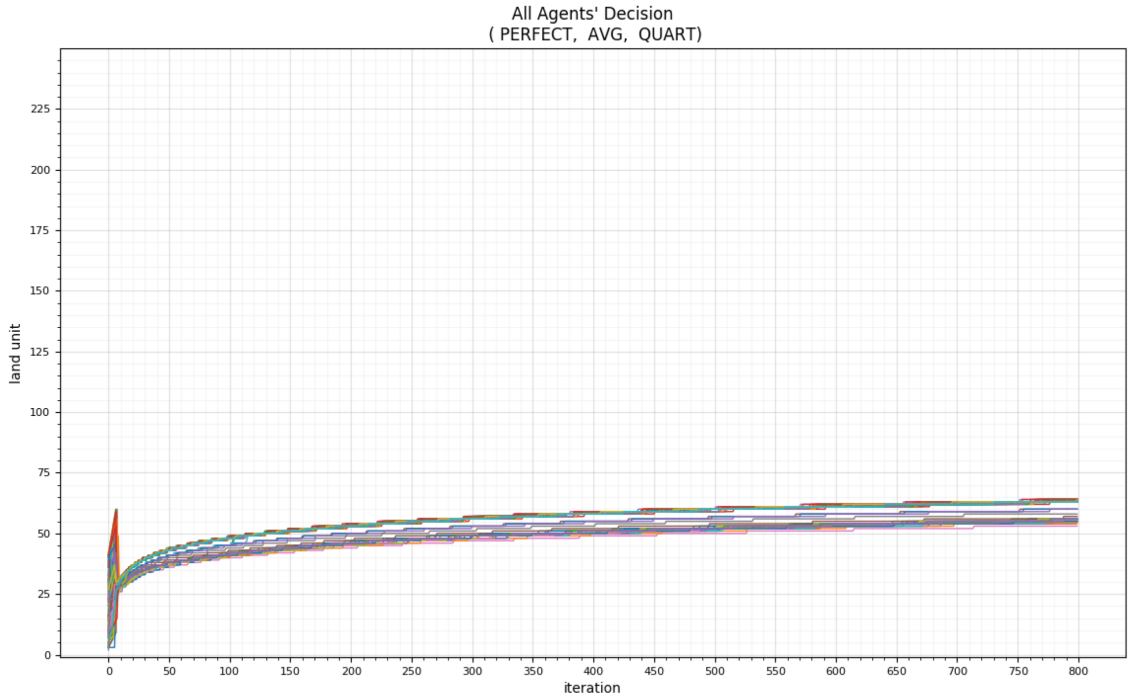

Figure IV-31. PERFECT-AVG-QUART strategy without using L3

Compared to other strategies and conditions tested in the current study, these three strategies yield the highest average profit (62.01) with the standard deviation of decision at 3.03. The similarity between these three combinations are the PERFECT (MSG-A) and QUART (MSG-C) strategy.

In the previous research (Mahardhika et al., 2016), it was found that in most of the time, human is not aware of the third layer. This is understandable because in normal situation, human will use the simplest way of thinking in solving problem, to reduce mental load (Kahneman, 2011). Besides, the deeper the layer an agent uses, the more effort is needed to be aware of it (Stiller & Dunbar, 2007). In the current study it is found that the highest profit can be reached exactly when the agents do not consider the third layer. This supports the claim that human cognition is efficient and yet still accurate (Matlin, 2012). However, it can be interpreted that L3 plays a role as the 'brake' to prevent overconsumption. With L3, agents are more considerate of others, therefore there will be less chance to overconsume the land.

As seen in the base case (Figure IV-2), without the second layer and third layer, the agents will overconsume the land. When the second layer is used without the third layer, the average profit becomes slightly higher than the simulation with the third layer. Since higher profit can lead to overconsumption, we can see that the lower layers play a very important role in controlling the society. This is an important result because such control does not require any force from authority, but instead, only relies on the awareness of the agents towards other agents' expectation. Therefore, another possible way to avoid overconsumption beside having an authority, is by providing a support for awareness towards the lower layers.

4.2.6 Composition of agents

In the default scenario the ration between greedy, balanced, and modest agents is 3:3:4. Simulations with different agent-composition ratio have also been conducted. The first composition is 8:1:1 (greedy-dominant), followed by 1:1:8 (modest-dominant). The reason why such compositions are chosen is the resemblance of real situation. Purely homogenous society might not exist. However, it is still possible that a society is dominated by a certain type of people. Figure IV-32 and Figure IV-33 show the base case (decision without considering L2 and L3) for greedy-dominant and modest-dominant society, respectively. Figure IV-34 shows the full-scale graph for modest-dominant society.

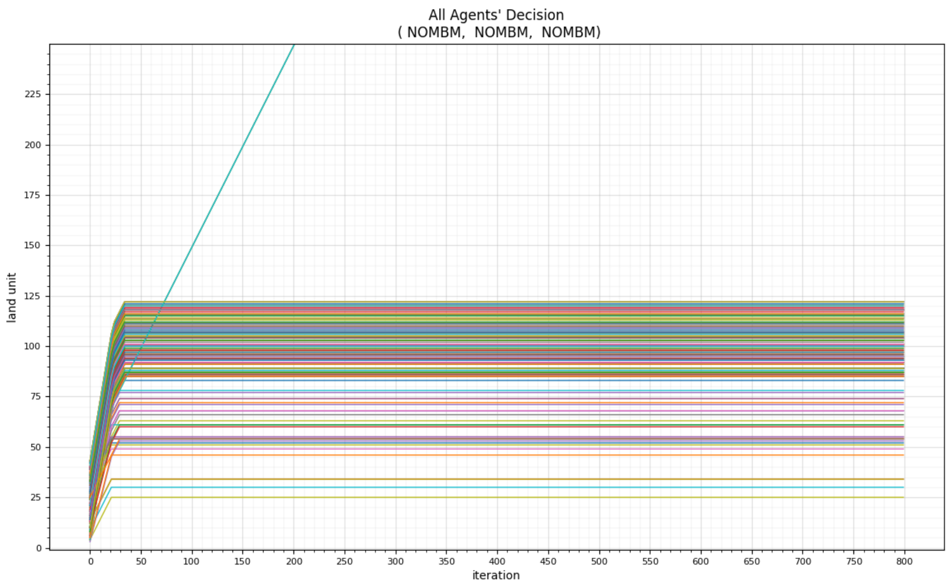

Figure IV-32. Base-case for greedy dominant society

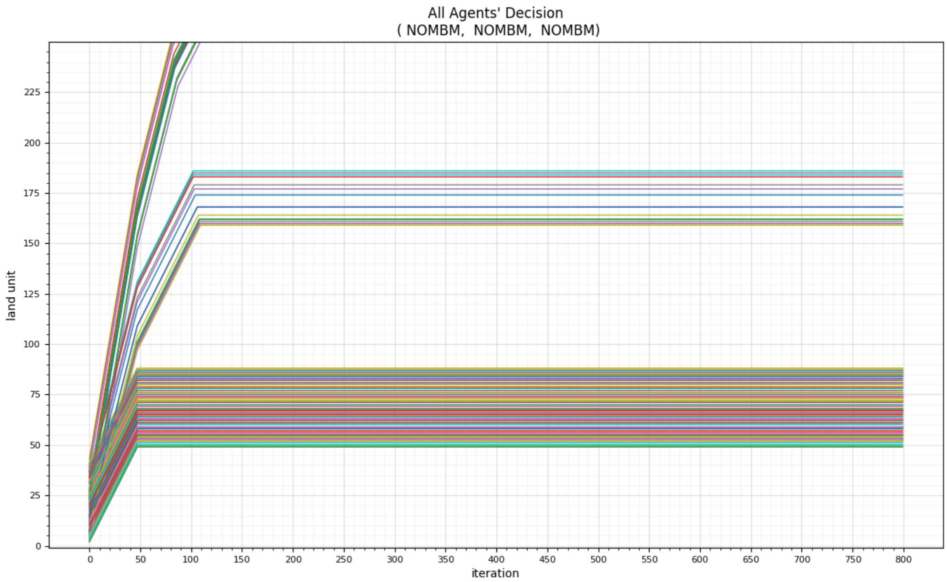

Figure IV-33.Base-case for modest dominant society

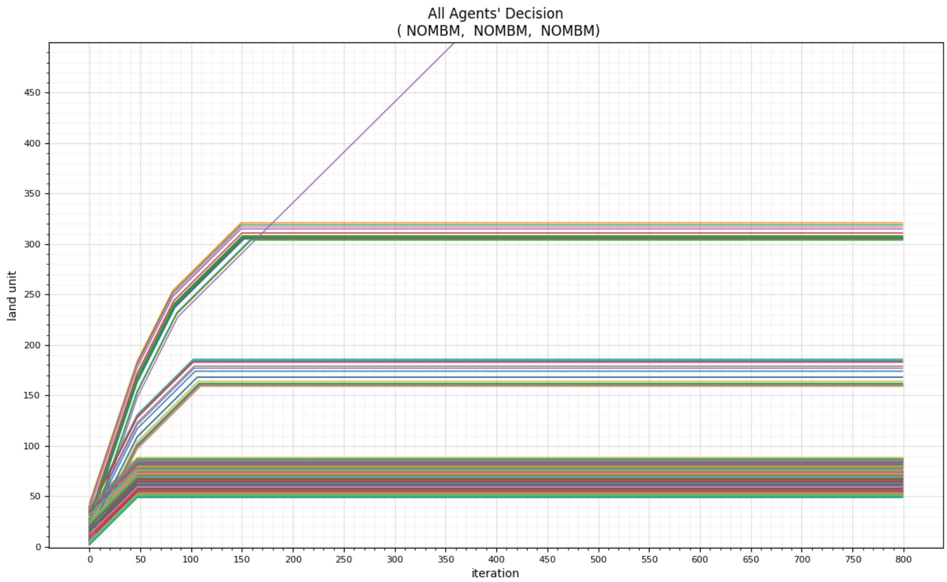

Figure IV-34. Base-case for modest dominant society (full scale)

From the above cases, one interesting pattern is the existence of 'free-rider'. In economics, free-rider problem occurs when those who benefit from resources, goods, or services do not pay for them (Baumol, 1952). In the context of our study, a free rider is defined as the minority group who keep adding the land while most of the society already stop acquiring more land. In the greedy dominant case, three free-rider agents were found (indicated by the top blue line in Figure IV-32). In this case, these free-rider agents share two characteristics. The first is their low initial land size of 1 unit. The second is that they are all greedy agents. In the modest-dominant case, the top purple line shows one such agent. It has 4-unit initial land size and the greedy characteristic.

Free riding problem is found more in the modest-dominant society. Since most of the agents are modest, they stopped quickly when they notice that the land quality starts to decrease. The minority greedy agents use this opportunity to keep acquiring more land up to more than 300 units per agent. Interestingly, in both greedy-dominant and modest-dominant society, the final average profits are no so different. Due to overconsumption, they yield only 6.12 and 7.02 units of profit in the end, respectively. The profit difference is shown in Figure IV-35. The difference however is in the convergence of decision. In the final iteration, the standard deviation of decision in the greedy dominant is 27.71 units, while the modest dominant has 74.35 units.

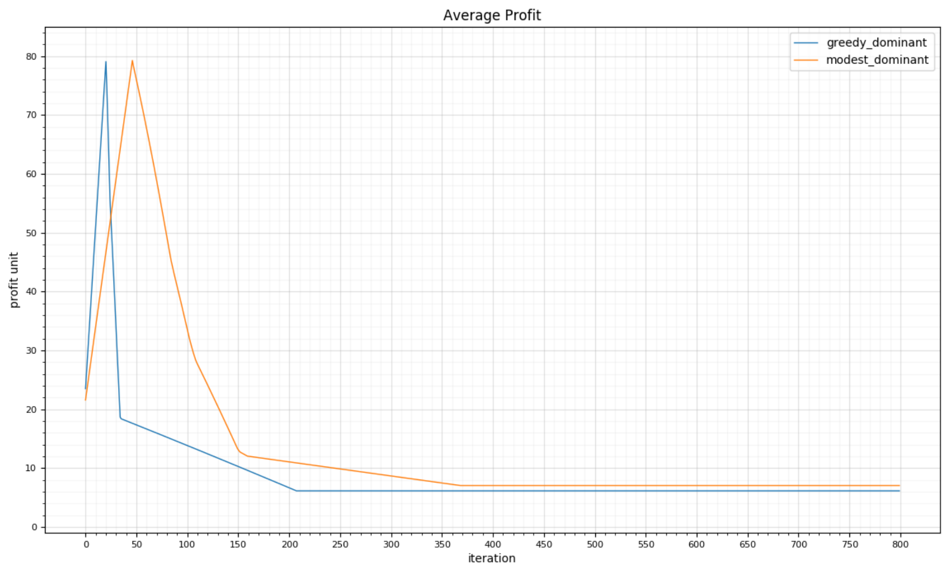

Figure IV-35. Profit comparison between greedy dominant and modest dominant society in the base case

After simulating the base case, simulations with all the 48 strategies were conducted. The complete graphs are shown in Appendix B and C. The norms in the final iteration are shown in Figure IV-36 and Figure IV-37.

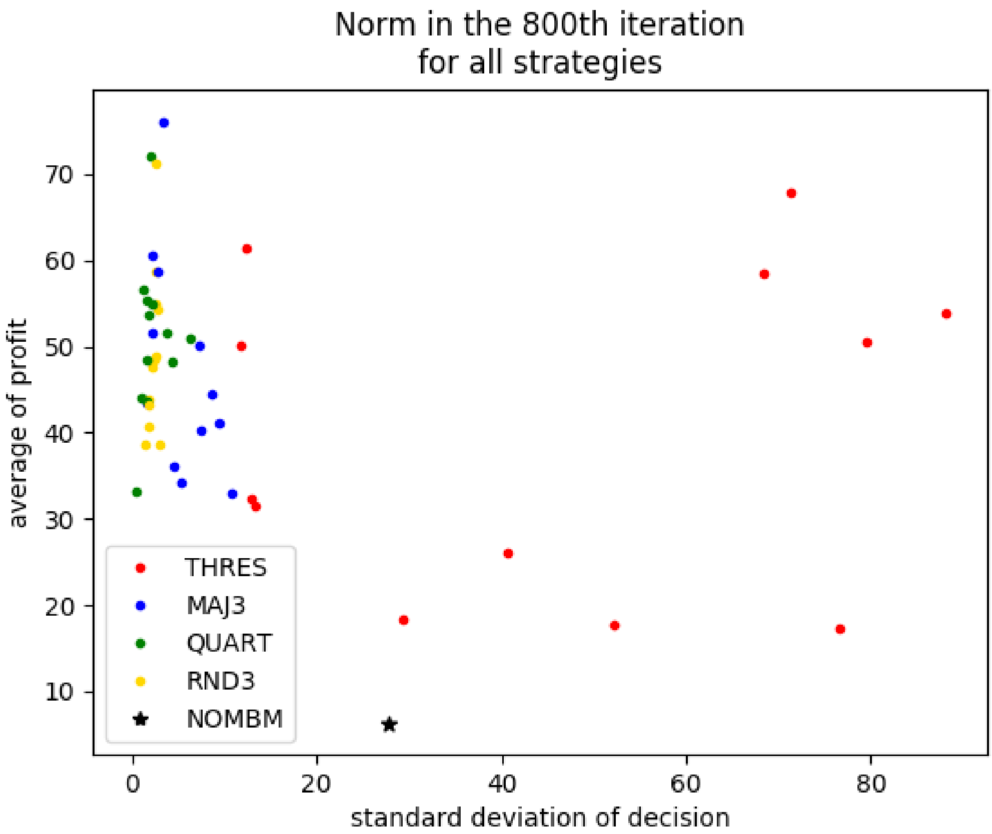

Figure IV-36. Norms of the greedy dominant society in the 800th iteration

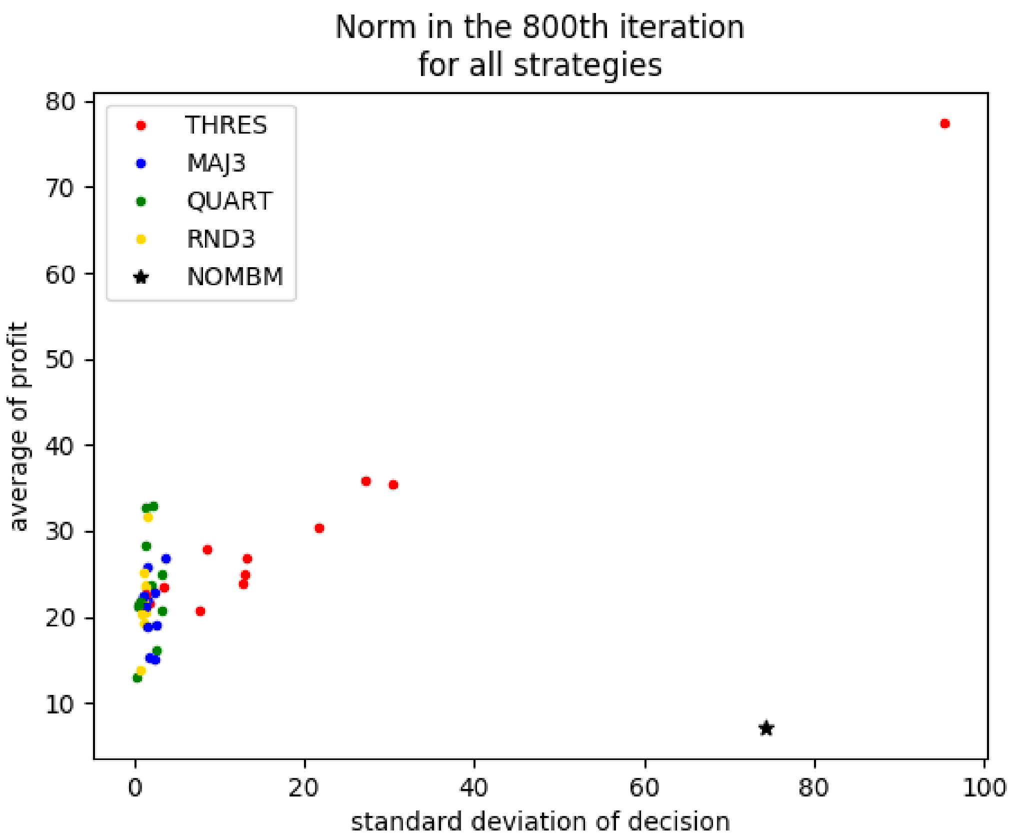

Figure IV-37. Norms of the modest dominant society in the 800th iteration

From the above result, it can be concluded that indeed the modest society are more controlled. The combination of modest agent domination and awareness to the lower layers prevent the society from overconsumption in the long run.

In both cases however, it is still clear that any mental subgrouping strategy still performs better in terms of profit and convergence of decision.

4.2.7 Network topology

In this simulation, different network topologies are used to see their impact towards norm emergence. There are three network topologies used in this simulation. In all of these simulations, the number of partners is varied among agents, with the average of 30. The network is also bidirectional. If an agent A can observe B, it means that B can also observe A. The first topology is generated by is Watts-Strogatz model (Watts & Strogatz, 1998). This is a random graph generation model that produces graphs with small-world properties. Figure IV-38 shows the result. The different colors represent strategies of the MSG-A.

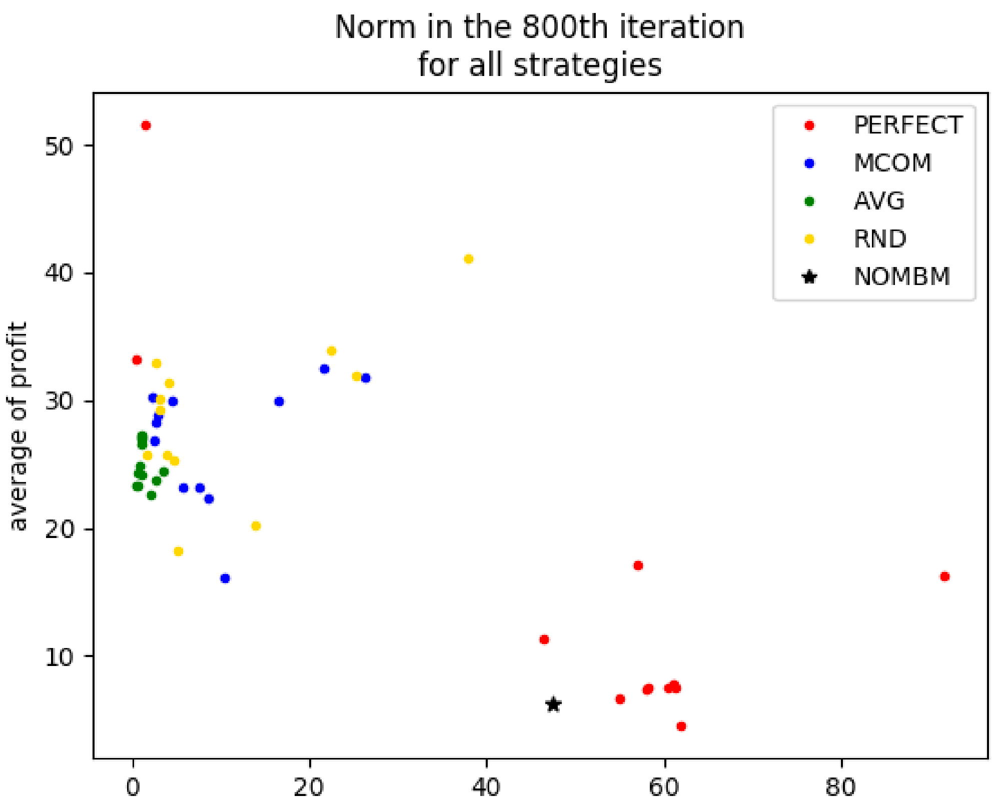

Figure IV-38. Norm emergence in a small-world network (MSG-A)

The second topology is a random graph generated by Erdos-Renyi model (Erdős & Rényi, 1960). The result is shown in Figure IV-39.

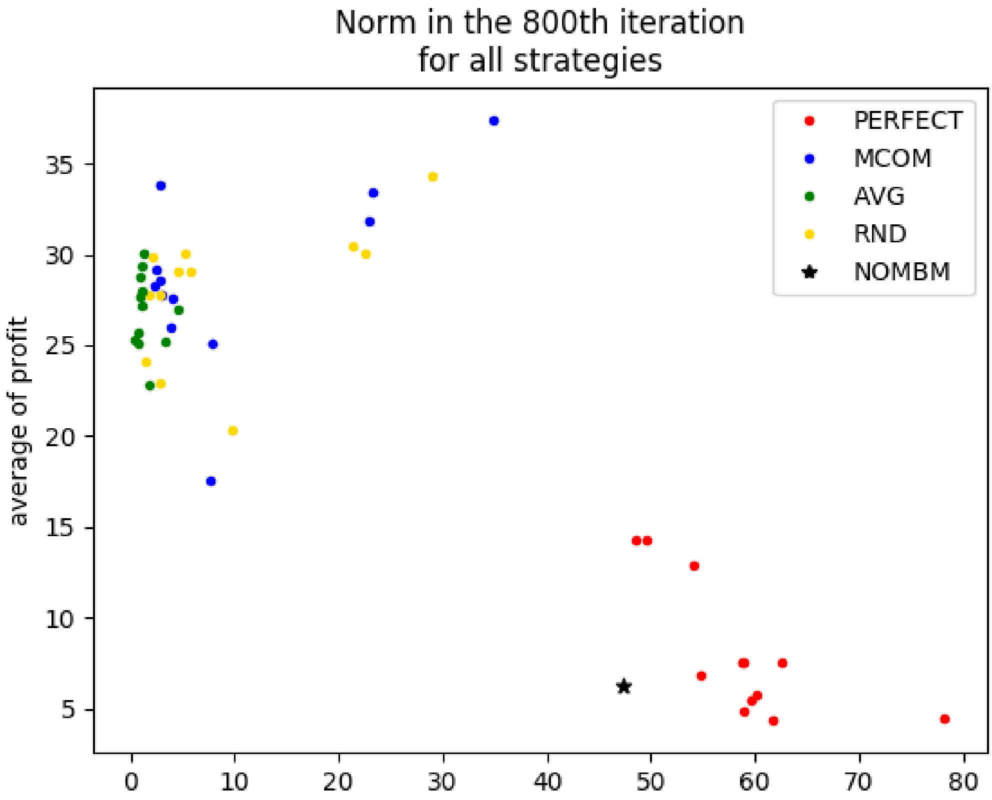

Figure IV-39. Norm emergence in a random network (MSG-A)

The third topology is a graph generated by Barabasi-Albert model (Albert & Barabási, 2002). This is an algorithm to generate a random scale-free networks. The main characteristic of such a network is that it contains a few main hubs that has unusually high degree as compared to other nodes of the network. The result is shown in Figure IV-40.

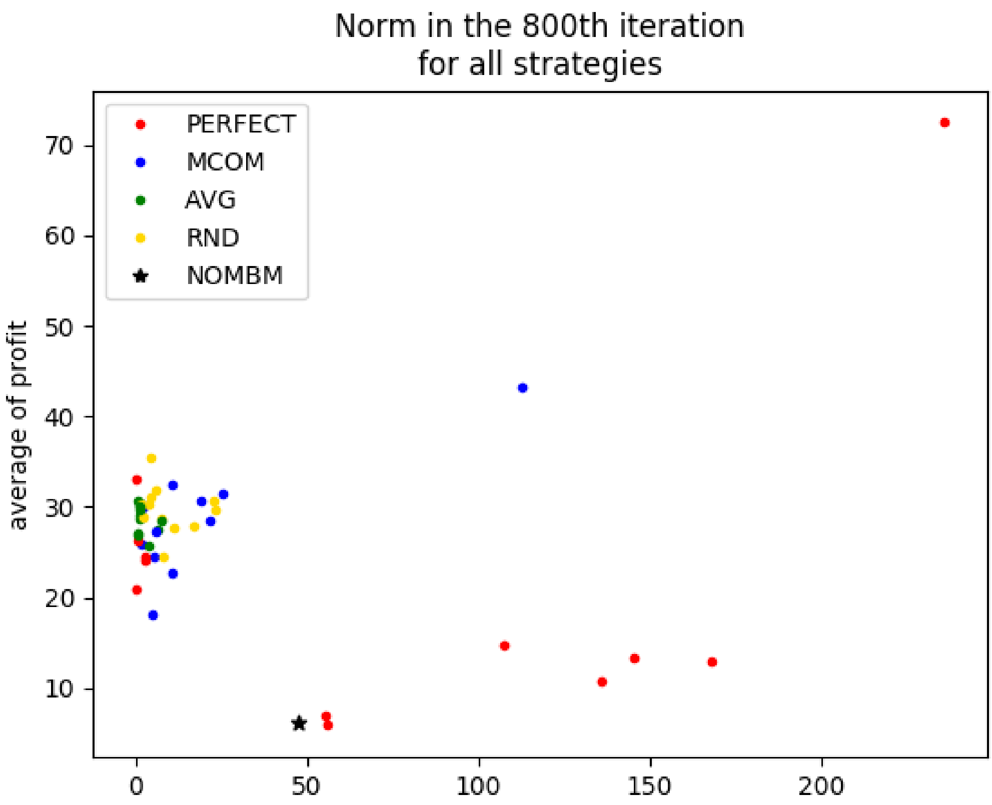

Figure IV-40. Norm emergence in a scale-free network (MSG-A)

In general, the results from the above three topologies are similar. Most of the red dots (the PERFECT strategy for MSG-A) have a low convergence. Such a phenomenon was not found in other cases. One similar case was the simulation with low number of partners, as explained in Section 4.2.4. Due to low number of partners, the norm emergence becomes very sensitive to the strategy in MSG-A. In the above three simulations, the number of partners are 30 on average, with 15 at the lowest and 92 at the highest. Even though the number of partners is not uniform, it seems that a low average number of partners still makes the emergence sensitive to the strategy in MSG-A.

Another interesting result is the case in the scale-free network, shown by a red dot in the top-right side of Figure IV-40 (PERFECT-MCOM-RAND3). Among all other simulations, this has the highest average profit of 72.48, but also the lowest convergence, with the standard deviation of 235.92. The agent with the highest profit acquired 2,098 units of land. The emergence of this strategy is shown in Figure IV-41.

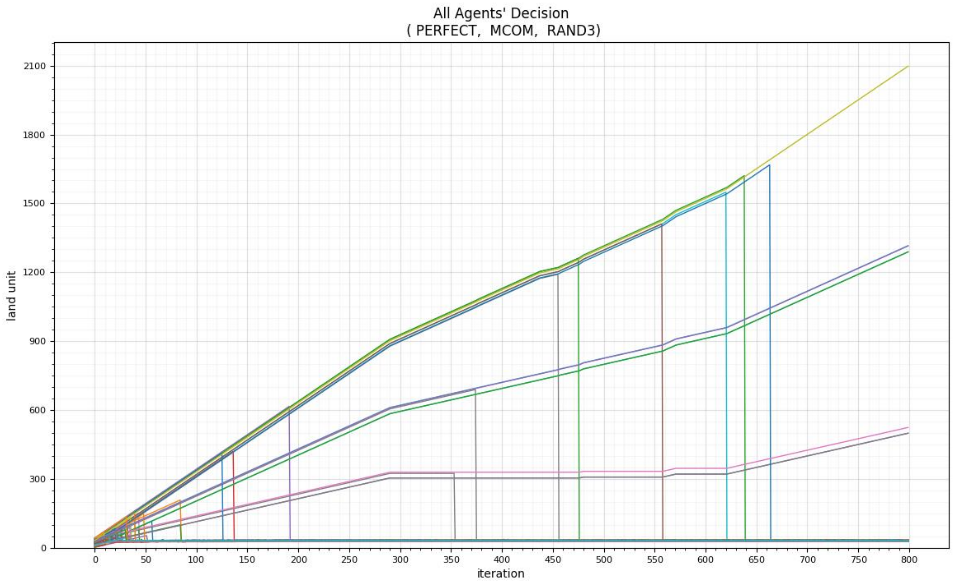

Figure IV-41. PERFECT-MCOM-RAND3 strategy in the scale free network

The agents with the 8 highest profit and their characteristics are shown in Table IV-3. Those agents share some similar characteristics, which are high norm threshold but low number of partners relative to the average number of partners. Even though there are many other agents with similar characteristics that have low profit, this result shows an important insight. In a scale-free network, the agents with few partners but high norm threshold have the possibility to overconsume resources, regardless their personalities.

Table IV-3. Agents with the highest profit in the scale-free network

Agent	Land	No. of Partners	Norm Threshold	Personality
agent198	2098	16	8	greedy
agent179	1316	17	7	balanced
agent194	1315	16	8	balanced
agent159	1289	17	7	balanced
agent182	1289	17	8	balanced
agent186	524	16	7	modest
agent154	499	20	8	modest
agent167	499	16	7	modest

4.3 Interpretation and Implication

In Chapter I, a sample case of societal phenomena caused by technological innovation was explained. The case was about online disinhibition effect in social media use. In regards to this case, the findings from the current study can give us some insight.

The key findings and insights from the simulations are as follows.

4.3.1 Norm emerges following the tipping concept

Firstly, once the agents interact, it only takes a few iterations for them to converge. This is indicated by the sudden drop of standard deviation that always happens early in the simulation. After this major convergence, the agents will make smaller adjustment to try to conform more with each other. In some cases, the agents can increase their land size together in a similar rate. This phenomenon can happen due to the awareness to the lower layers. When the agents do not pay attention to the expectation of other agents, the society as a whole overconsume the resources.

4.3.2 Importance of supporting awareness to the lower layers

The second insight is, when agents only have few partners (relative to their norm threshold), it becomes difficult for them to find a norm candidate. The norm candidate that they will get will heavily rely on how they infer the intention and expectation of other agents when communication fails. Even though in online interaction users seem to have many more observable partners, the reality is different. When reading Facebook or Twitter for example, they are limited by the screen space. Moreover, recent online media has an algorithm to selectively show the posts. These limits the users' ability to get enough information about the whole society.

From the two insights above, the key point to intervene such 'overconsumption' situation and to allow the society to have a norm is by focusing on the awareness on the lower layers. Even in face-to-face interaction, humans are rarely pay attention to lower layers, especially the third layer (Mahardhika et al., 2016). Due to the factors mentioned above, awareness to the lower layers become much worse.

4.3.3 Importance of supporting inference strategy

The third insight is from the mental subgrouping strategy. Form the result of discussed in Section 4.2.2, we can see that mental subgrouping process using the 'random pick' strategy shows less sudden change in the emergence of society. Since one key point of norm dynamics is tipping (sudden change), it can be suspected that mental subgrouping is not done by random process, but rather through a more systematic process (e.g. based on similarity or centrality). Recently, online media try to prioritize topics or posts to be shown to their user. Usually the algorithm is by choosing topics that are similar the ones that the user has watched, or topics that is trending. This algorithm creates a problem called 'filter bubble' (Pariser, 2011). This problem enhances self-confirmation bias among internet user because user will see posts or topics that are in line with their interest. In the view of the insights from the current study, this filter bubble heavily influences mental subgrouping. In the current study, the posts or topics is represented by the norms in the simulation. Users will find similarity or centrality of those topics or posts. However, since those topics have been systematically chosen, the users have no choice but to create mental subgrouping based on what the system has chosen.

This is one important point for intervention. On the one hand, the algorithm to choose the post that will be shown to the users can be used to direct the society towards a certain trend. For example, instead of showing posts that are similar to users' interests, it shows posts that have been decided as 'good for the society'. However, on the other hand this is risky because the authority or institution may abuse this feature to serve their own view.

Another possible intervention is by letting the users view the posts or topics as it is, without sophisticated filtering algorithm. In this way, users' mental subgrouping will have less bias. One problem is that due to limited space of showing posts, online media are still forced to make prioritization of posts. One suggestion for these online media is to create a support for the users to see more balanced topics or posts.

4.3.4 Insight for the Online Disinhibition Effect (ODE)

In the case of online disinhibition effect, we can interpret the freedom in using the internet as the limited resources. Overconsumed freedom means that everybody behaves only according their own intention. Similar to the land in the simulation, nobody knows the limit of freedom, but when everybody overuses it, everybody will start to feel that the environment (the social media) becomes less comfortable. The norm that the internet users need to find is "how much freedom can I use in online media?".

In his work of ODE, Suler (2005) mentioned that there are six factors causing ODE. They are “dissociative anonymity”, “invisibility”, “asynchronicity”, “solipsistic introjection”, “dissociative imagination”, and “minimization of status and authority”.

All of them can be related to the process of updating the second and third layer. In “dissociative anonymity”, “invisibility”, and “disassociate imagination”, users separate themselves from their online being. They disassociate their intention (first layer) and the expectation towards them (third layer). In their mind, the expectation is directed towards their online presence instead of themselves. Therefore, their final action does not consider the lower layers, in particular the third layer.

In “asynchronicity”, users fail to have an immediate response from the other users when discussing about a subject. This disturbs the process of immediately understand what other people expect about the subject (second layer), also what other people expect from that particular user (third layer).

In “solipsistic introjection”, users tend to feel that everything they read in the internet ‘has merged’ into their mind. This is one form of self-confirmation bias. Users will assign a visual image of the person they are interacting with, solely from the limited information available through the screen, even from a short comment. This creates an inaccuracy in inferring the type of person they are communicating with. Thus, this also creates an inaccuracy in inferring other necessary information for the lower layers. The “minimization of status and authority” also has similar effect. Online users fail to recognize the different status of people they interact with, thus create an inaccuracy in the inference process.

In this sense, the ODE can be seen as a societal phenomenon where the users fail to make decision and action based on the lower layers of the mutual belief structure. As shown in the base case (Figure IV-2), when the lower layers are not considered, the whole society overuse the resources. In the ODE case, they overuse their freedom. It is necessary for the designer of the online media system to think about the support for L2 and L3 awareness to reduce ODE.

4.3.5 Insight for society of artificial autonomous agents

The findings in this study also give a valuable insight for creating a society of autonomous agents. First, by embedding the mechanism of mutual belief, autonomous agents like self-driving cars can quickly reach a convergence of behavior. With mental subgrouping behavior this can be reach without communicating with all other agents in the society, but instead only a portion of them is enough. This will reduce computational and communication cost between agents. Reaching a convergence quickly is good for the whole society since behavior of other agents will be more predictable.

Second, it is found that proportion between number of partners and norm threshold determines the norm candidates. Unlike human, artificial autonomous agents like self-driving cars do not have a fixed threshold of norm. Therefore, it becomes important for the designer of those agents to determine this value when implementing mutual belief structure.

Chapter V
LIMITATION AND FURTHER RESEARCH

This study tries to understand the mechanism of norm emergence from the perspective of individual member of the society. The understanding is necessary to get an insight of what kind of intervention is necessary to allow the society to reach a norm.

To reach the goal, however, several factors are not considered in the current study and need to be addressed in further research.

5.1 Emotion Factor

First of all, even though the current model is able to explain the cognition of a society from the perspective of individual members' cognition and their interaction, it does not take into account the factor of emotion. Emotion is recognized as one of the important factors in the construction of the so-called "collective mind" (Blumer, 1951; Freud, 1921).

Even though emotion can be modeled as a form of cognition (status of the layers), the current model is not adequate to model the relation between agent's emotion and the decision they make. Emotion in this sense can also include the interpersonal relationship between the agents. Humans tend to be affected by emotional closeness in weighing the importance of information from people around them. Interpersonal communication affects human attitudes and decision making (Asch, 1956; Katz & Lazarsfeld, 1955). Such a factor was not included in the current model. In the future research, the agents can be modeled to have different relationship, thus a different weight for considering the partner's expectation.

5.2 Variation of Mental Subgrouping Strategy

The second is about the variation of mental subgrouping strategy. As mentioned before, the mechanism of mental subgrouping is still unknown. It is suspected that it is based on similarity or centrality of the partner's cognition. In the current study, only majority rule, average, or quartile was used as mental subgrouping strategy. In the further research, it is necessary to find the factors and mechanism affecting the mental subgrouping process. Emotional factor and interpersonal closeness may also affect how mental subgrouping is done. Further empirical research need to be done to find out other strategies of mental subgrouping.

5.3 Network Dynamics

The third is about the partners of the agents. In real life, over time people move and change their partner. It is also possible that people only make friends only with those who have similar view or opinion (Hamm & V., 2000; Umphress, Smith-Crowe, Brief, Dietz, & Watkins, 2007). Therefore, there might be a feedback loop between the norm adopted from society by an agent and also the partners that this agent makes friends with. In the current study however, the network is fixed throughout the simulation. Agents cannot change their partners regardless the difference in their decision. And since the current network is not affected by the similarity of agents (characteristics, actions, etc.), such feedback loop is not modeled. Such factor should be addressed in the further research.

Chapter VI
CONCLUDING REMARKS

This research attempts to model the emergence of societal phenomena using a human cognition model. The model focuses on the bottom-up emergence aspect by implementing mutual belief and mental subgrouping. The model is implemented using a multi-agent social simulation. In particular, the simulation deals with the combination of different mental subgrouping strategies and the effect to the emergence of a norm.

There are several key novelties in the proposed models, as follows:

- Norm is viewed from the subjective perspective rather than objective perspective.
- The model follows the notion that norms consist of one's intention, empirical expectation, and normative expectation.
- The model gives a reductivist point of view. It is able to reduce a cognition of a society (the cognition behind the societal phenomena) into the cognition of the individual members of the society and relationship between them.
- The model incorporates the 'mental subgrouping' process, which is a natural process in human's mind when they interact with each other.

From the modeling and simulation, there are several key findings:

- Once the agents interact, it only takes a few iterations for them to converge. This is indicated by the sudden drop of standard deviation that always happens early in the simulation. After this major convergence, the agents will make smaller adjustment to try to conform with each other. In some cases, the agents can increase their land size together in a similar rate.
- Mental subgrouping process and awareness to the lower layers plays an important role in the norm emergence in the society.
- Mental subgrouping process using the 'random pick' strategy shows less sudden change in the emergence of society. Since one key point of norm dynamics is tipping (sudden change), it can be suspected that mental subgrouping is not done by random process, but rather through a more systematic process (e.g. based on similarity or centrality)

- When agents only have few partners (relative to their norm threshold), it becomes difficult for them to find a norm candidate. The norm candidate that they will get will heavily rely on how they infer the intention and expectation of other agents when communication fails.
- The awareness to the lower layers acts as a brake to control the society and prevent overconsumption of resources

For the presented case study of the Online Disinhibition Effect, the findings in this research supports the suspected cause mentioned in the original work about ODE. Lack of awareness to the lower layers allows people to overconsume the public resources, in this case the freedom of speech and act in the online media. The suggestion proposed from the current study is to provide support for good awareness towards the lower layers of mutual belief structure.

As for limitation of this study, there are three points:

- Emotional factor
- Variation of mental subgrouping strategy
- Network dynamics

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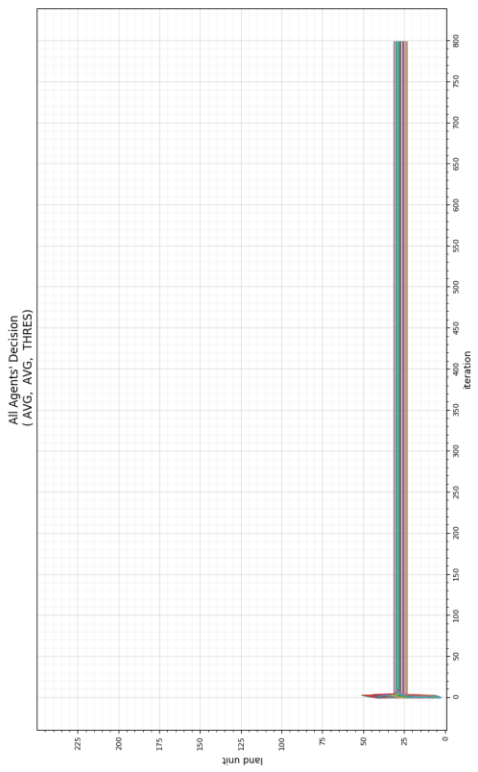
APPENDIX A
Norm Emergence for All Strategies in The Default Scenario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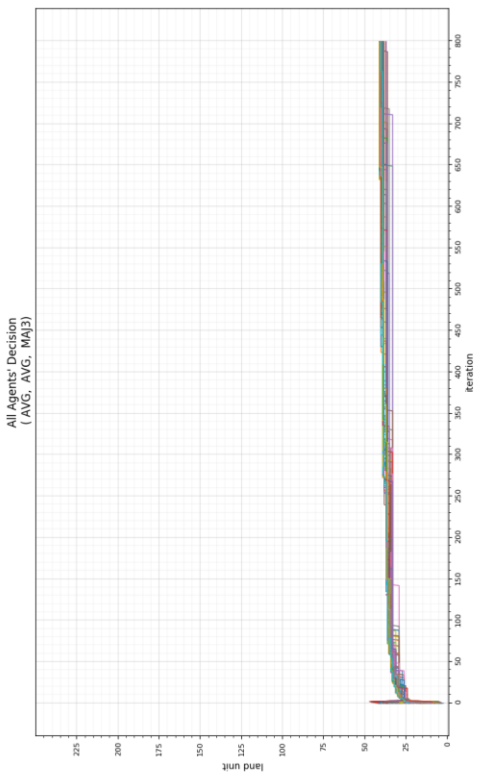
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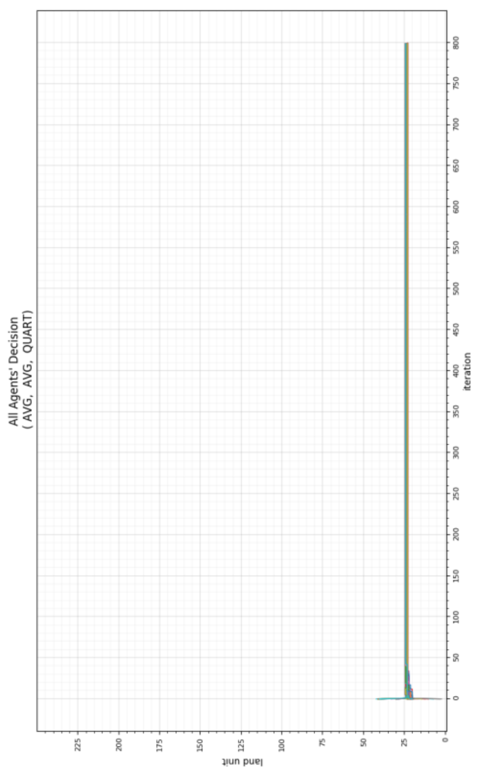
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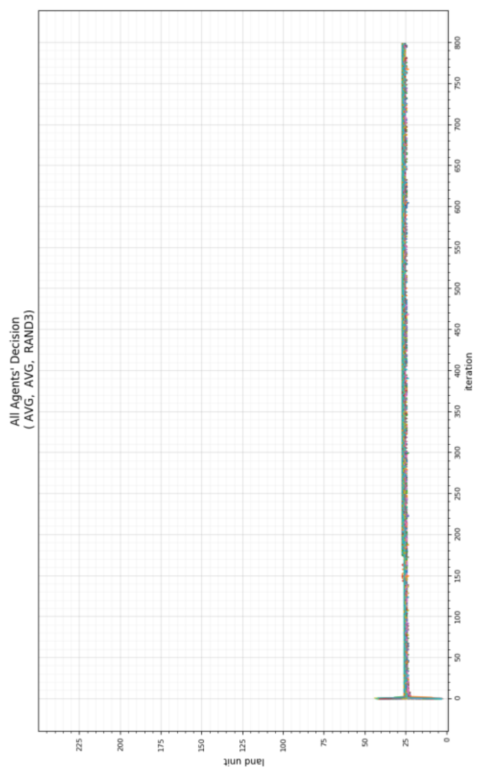
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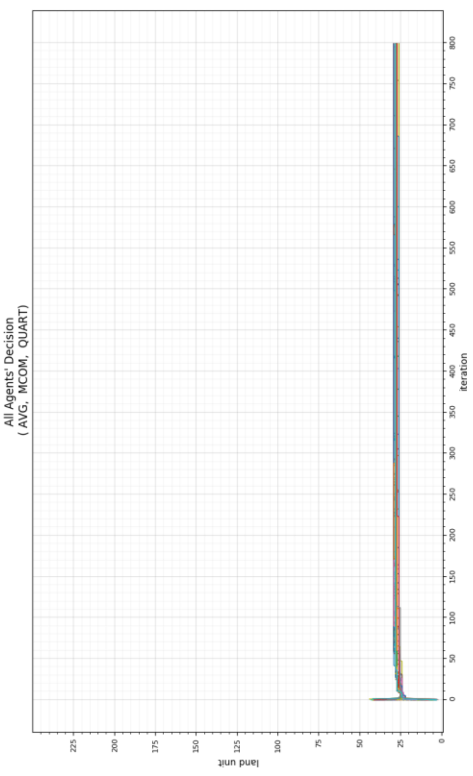
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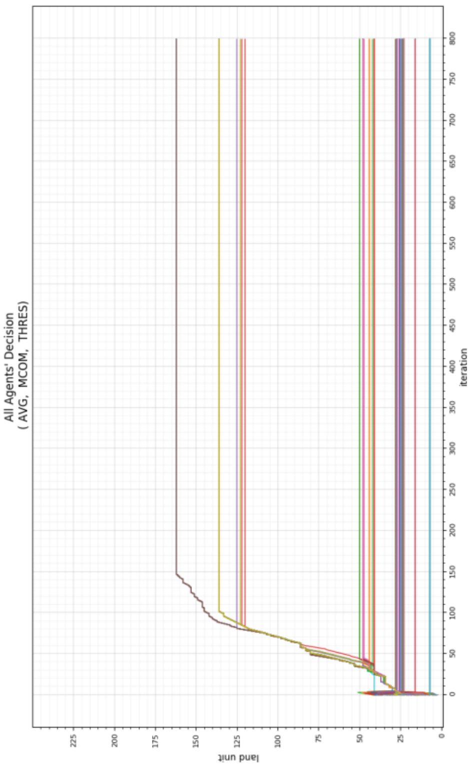
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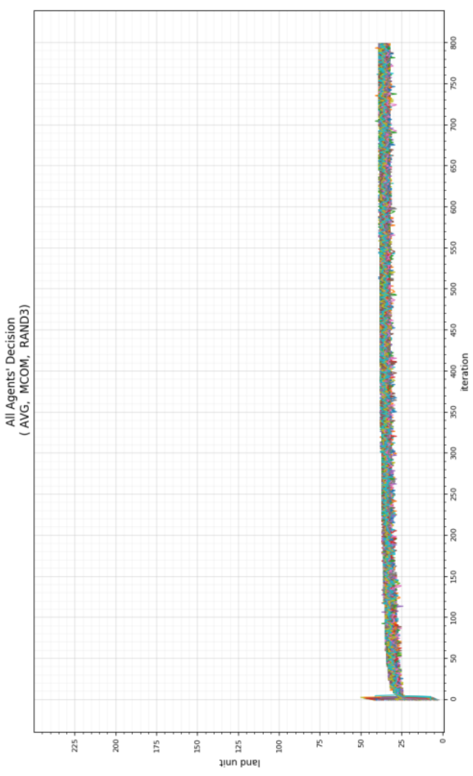
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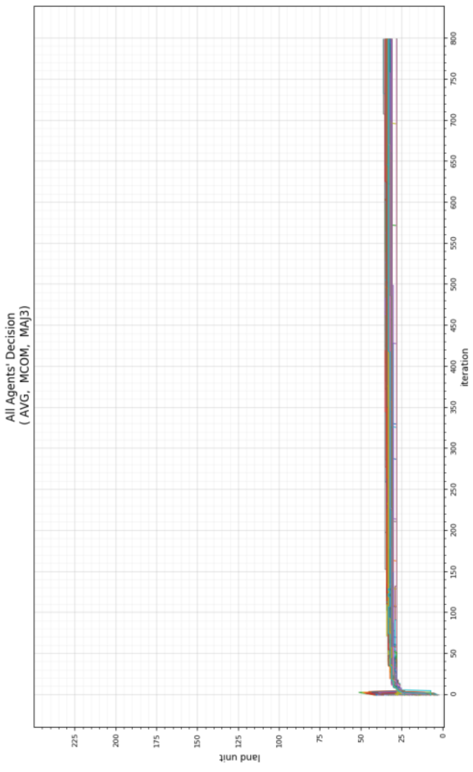
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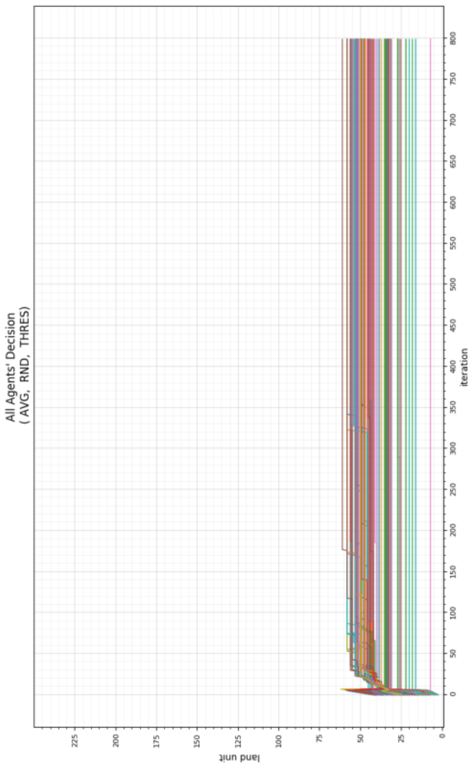
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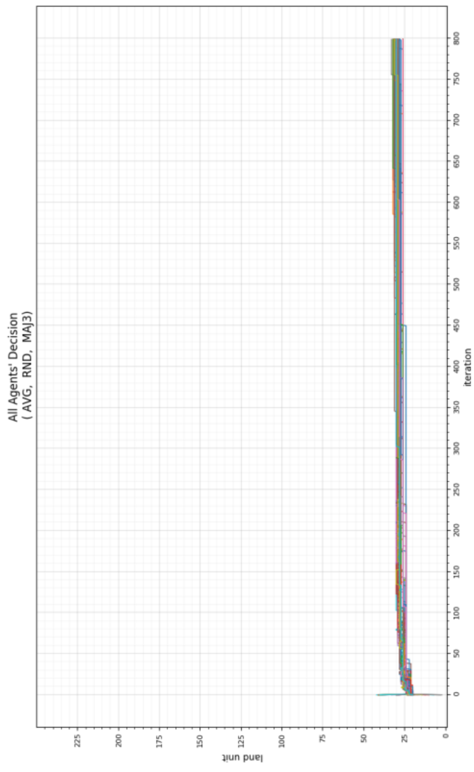
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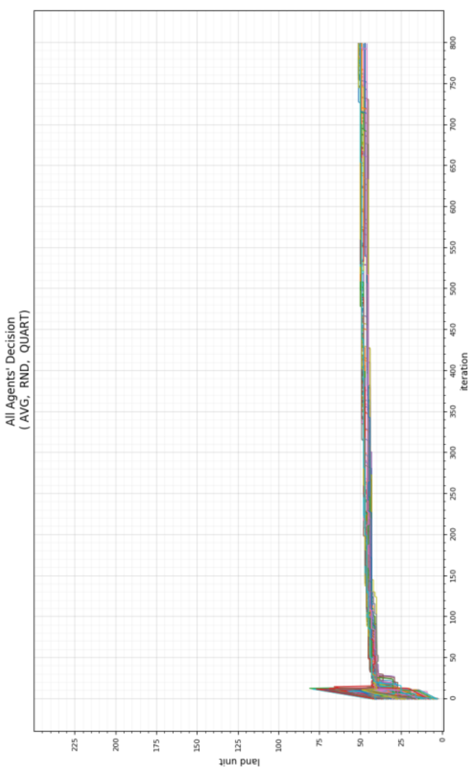
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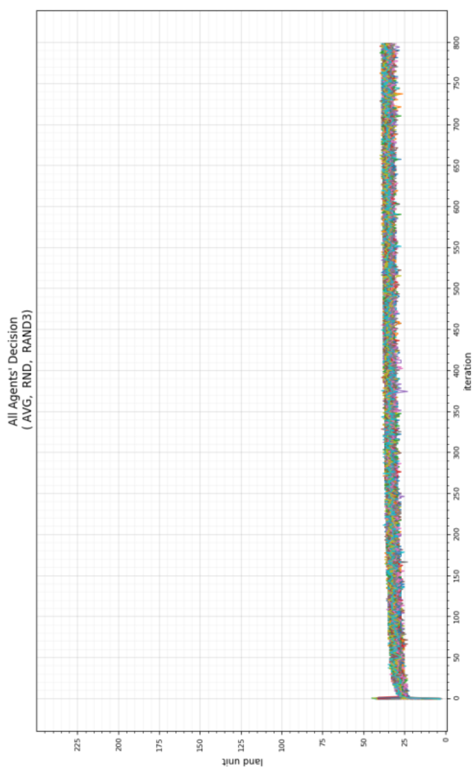
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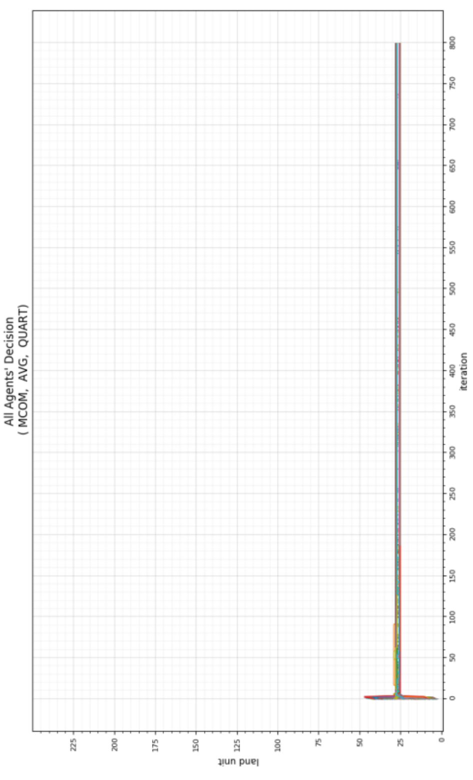
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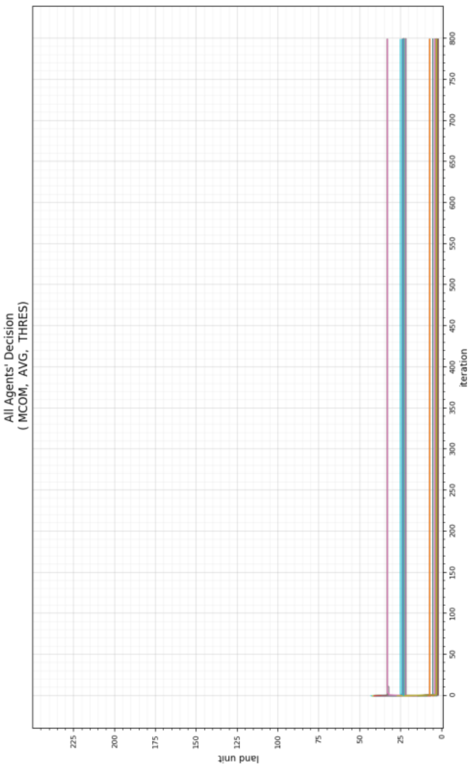
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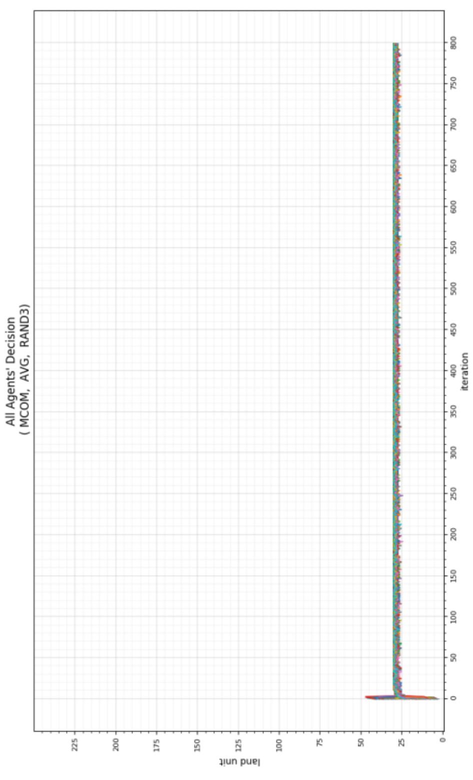
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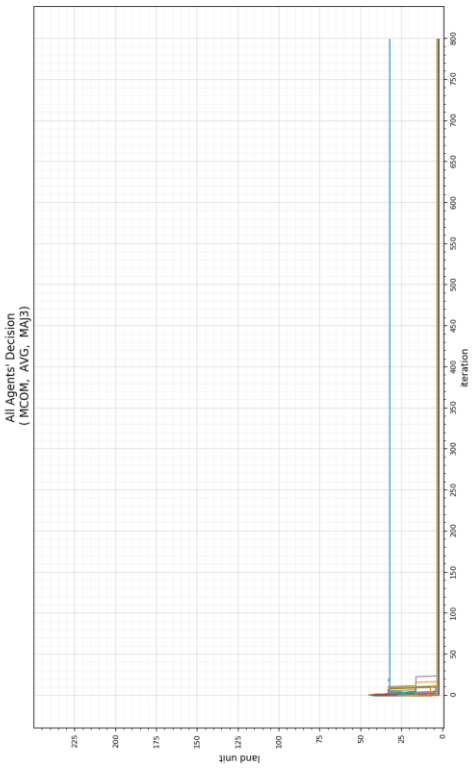
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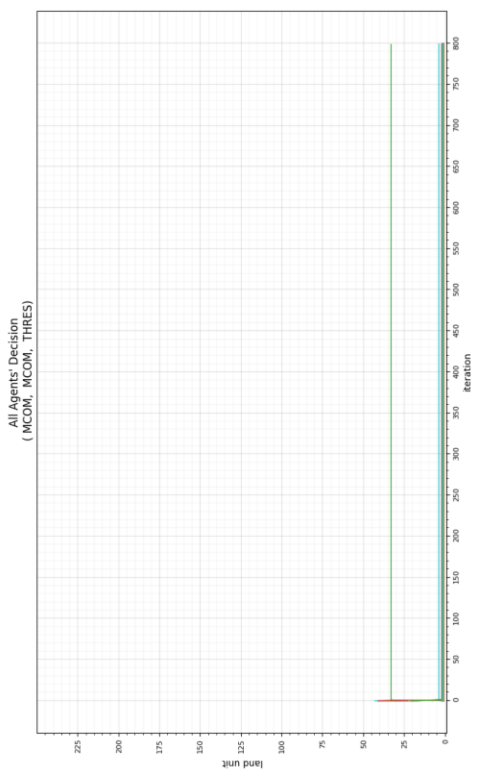
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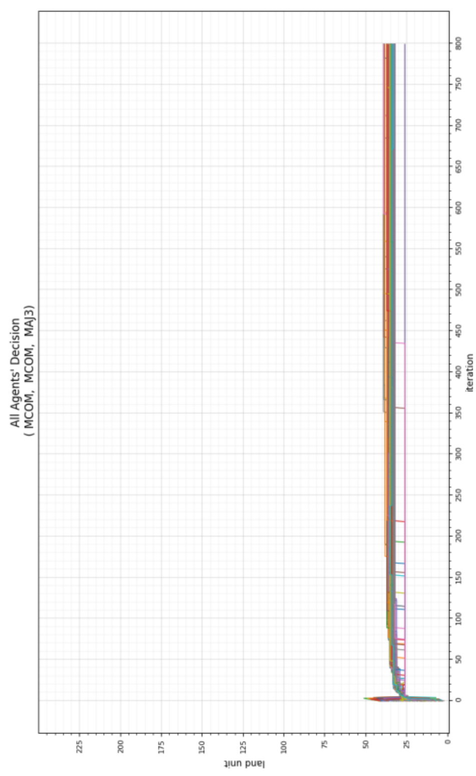
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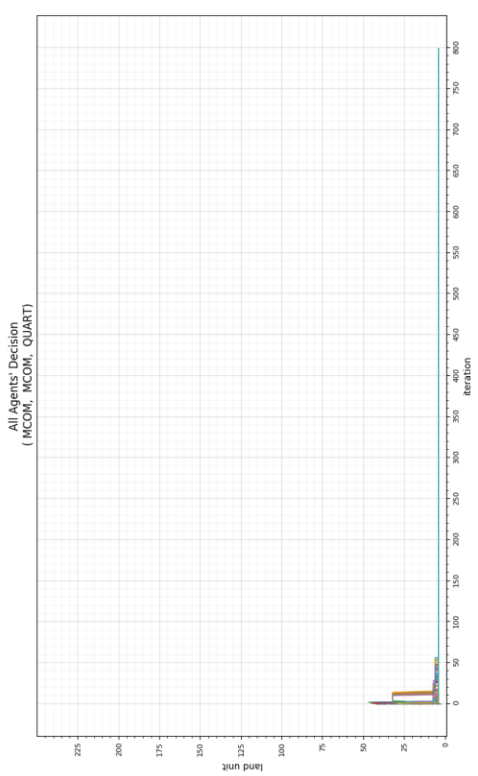
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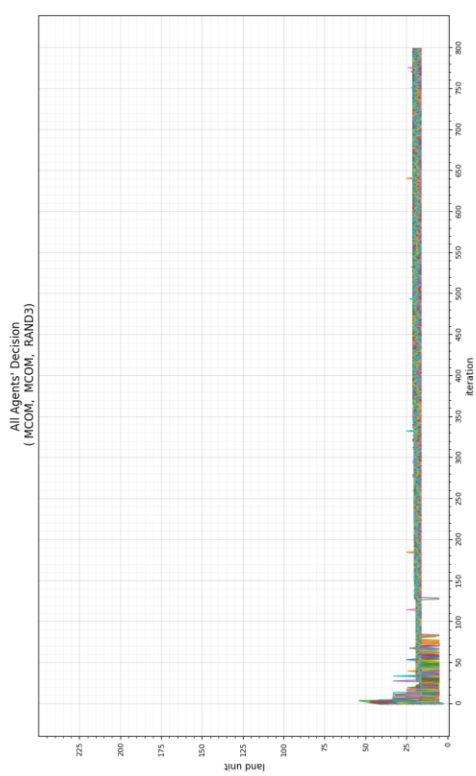
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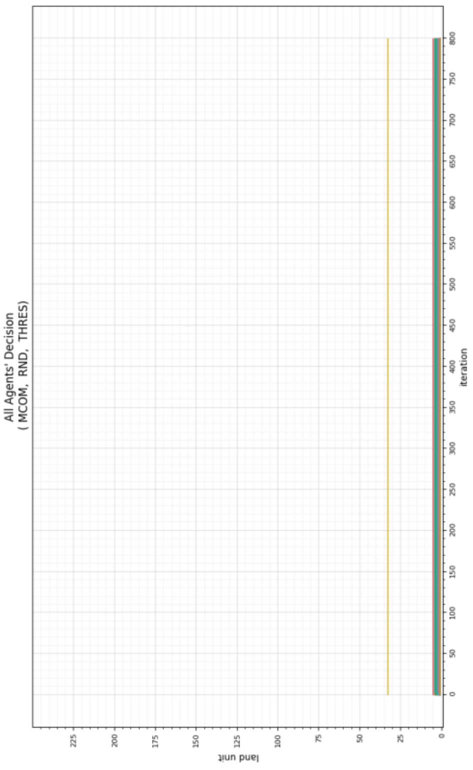
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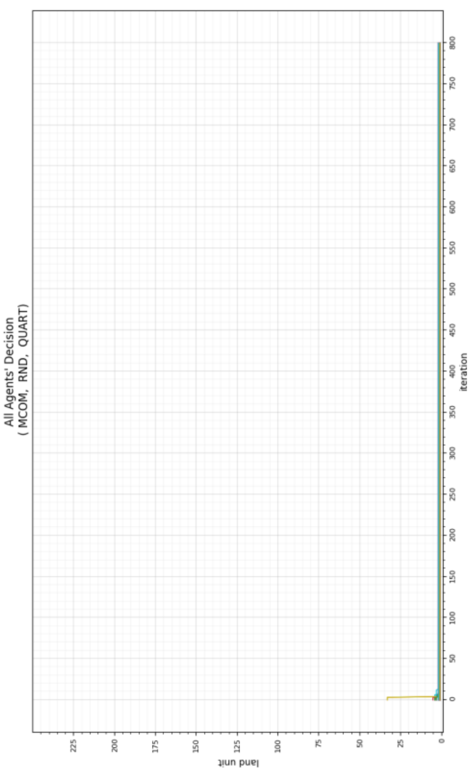
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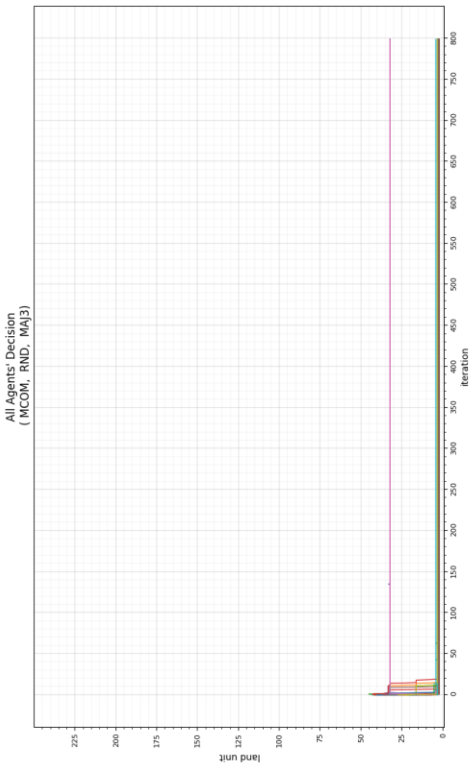
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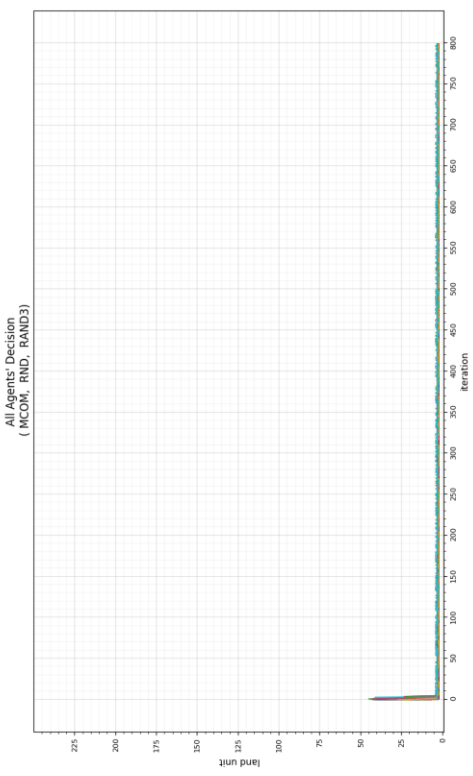
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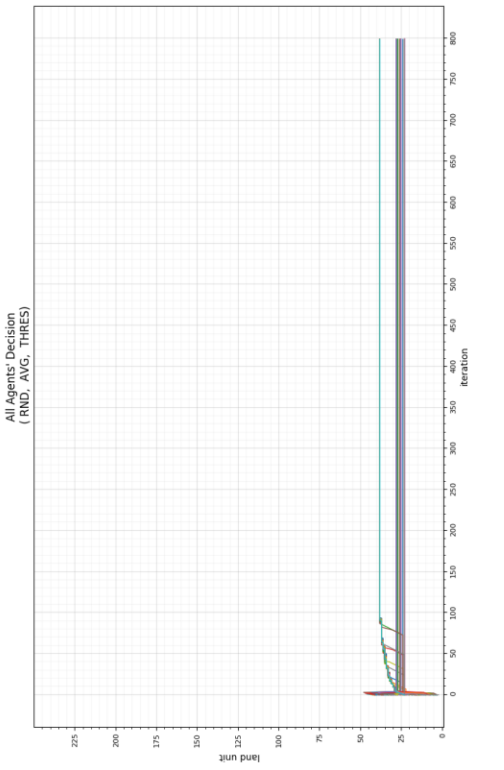
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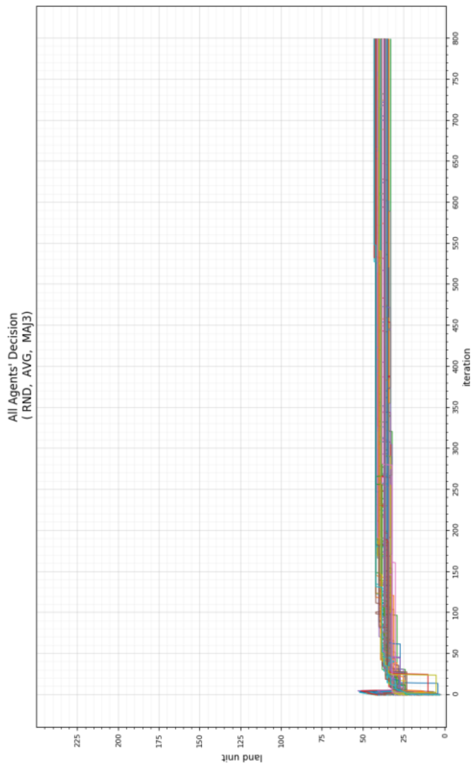
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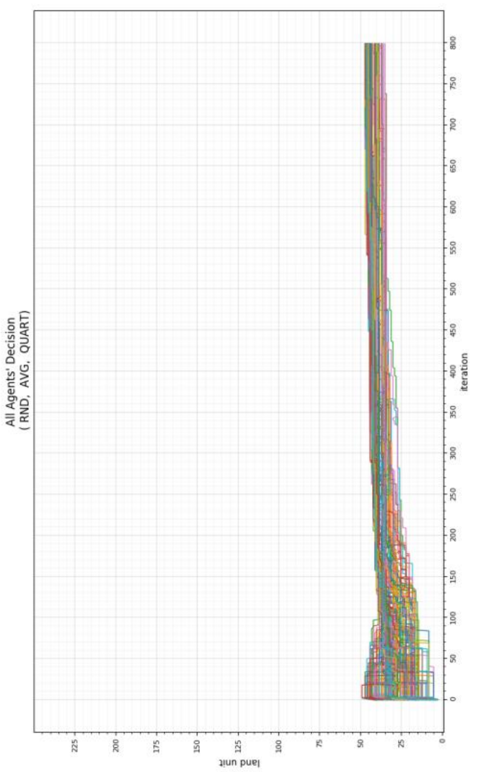
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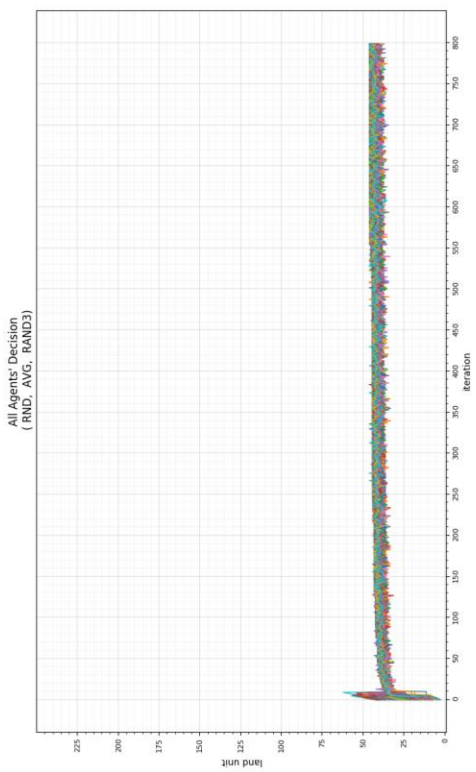
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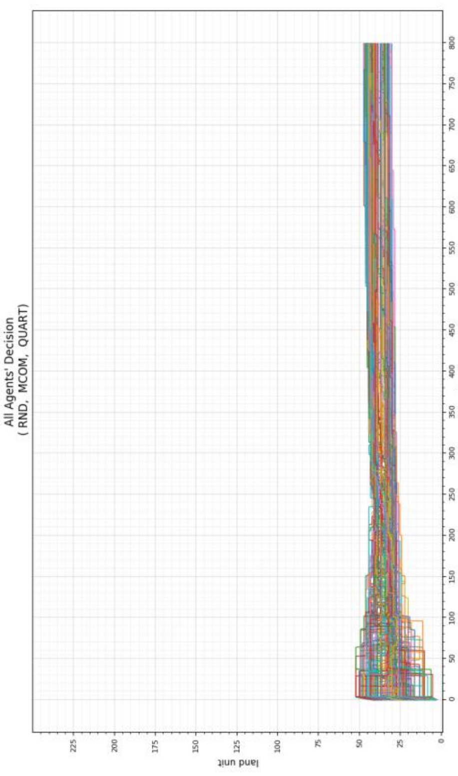
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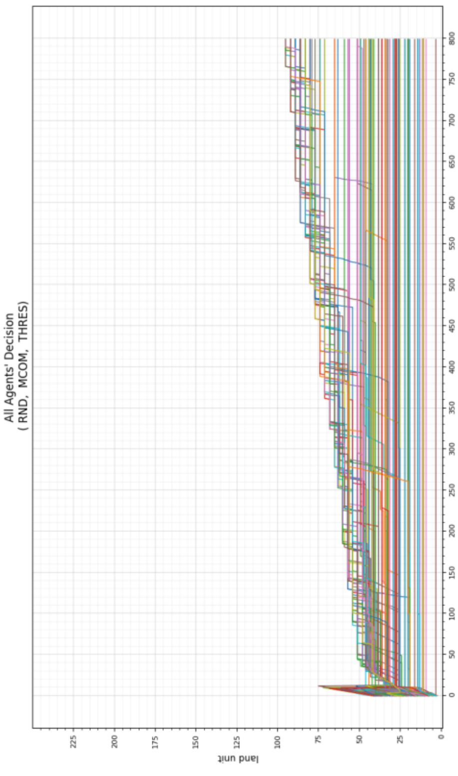
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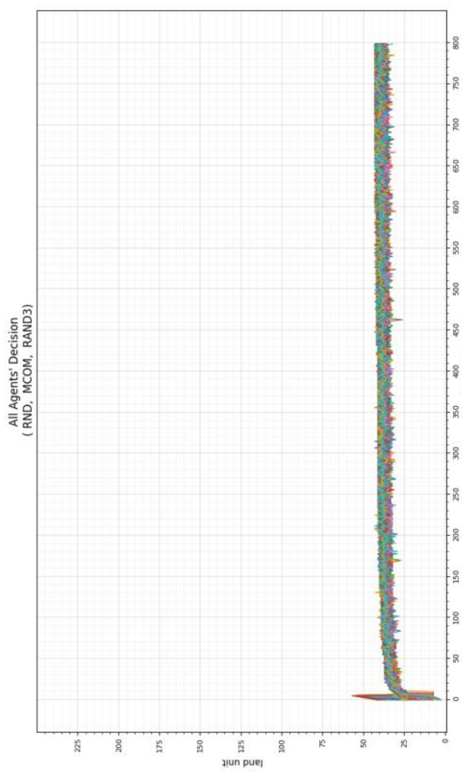
land unit
iteration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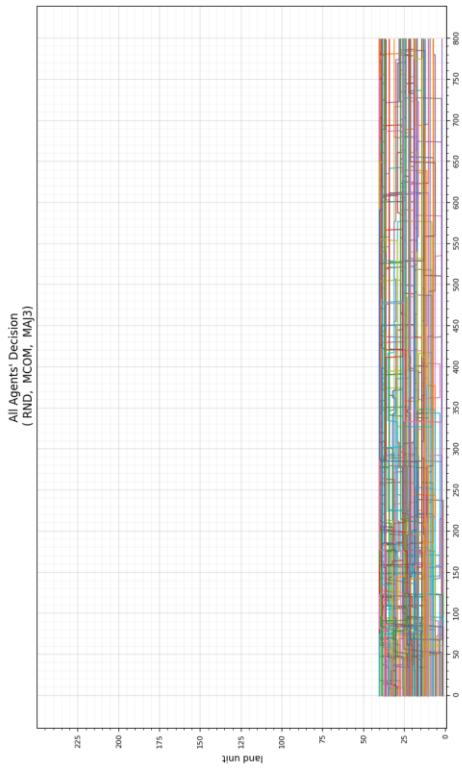
land unit
iteration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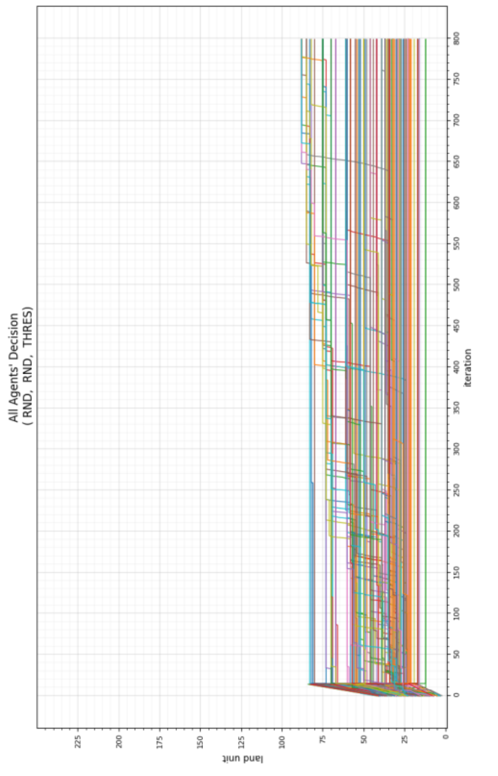
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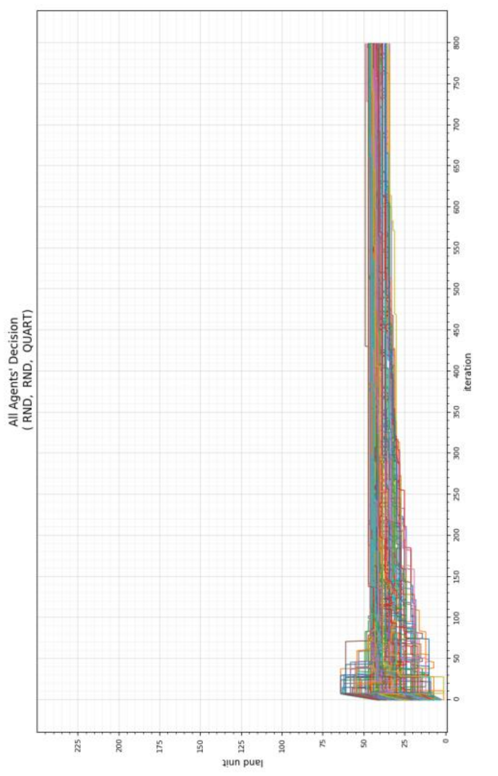
land unit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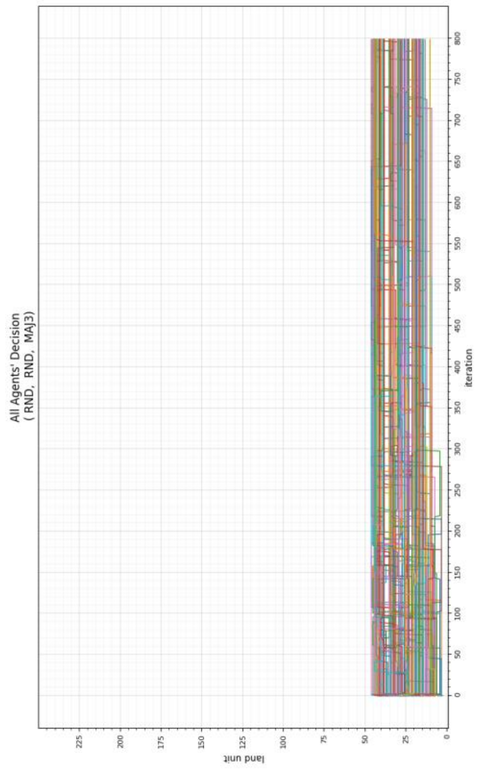
iteration
land unit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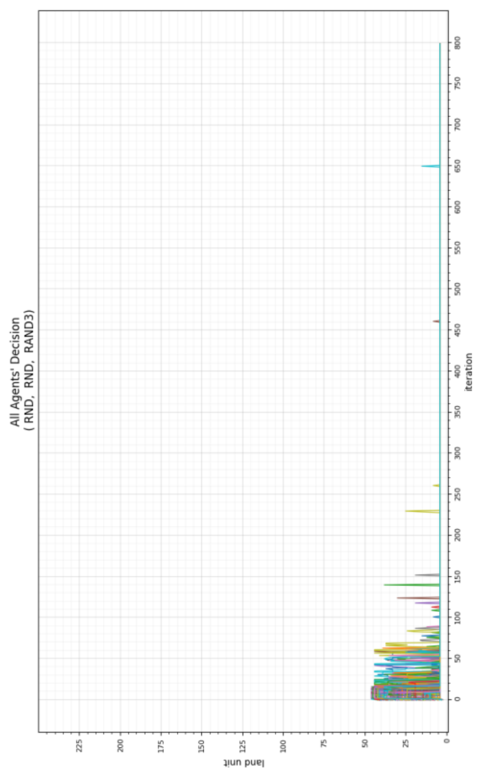
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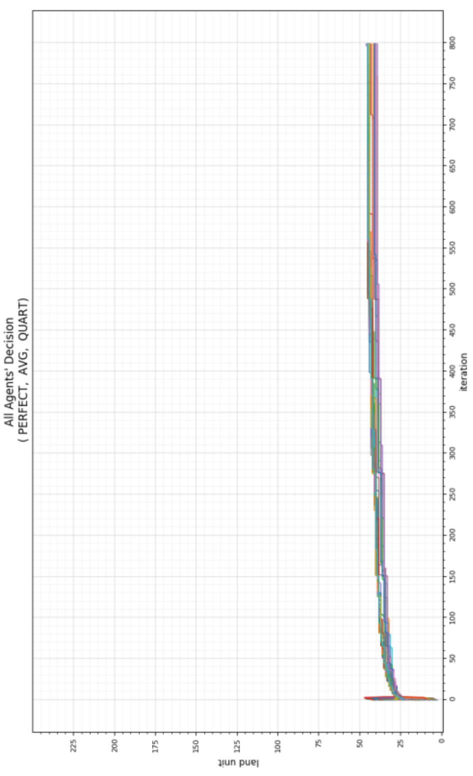
land unit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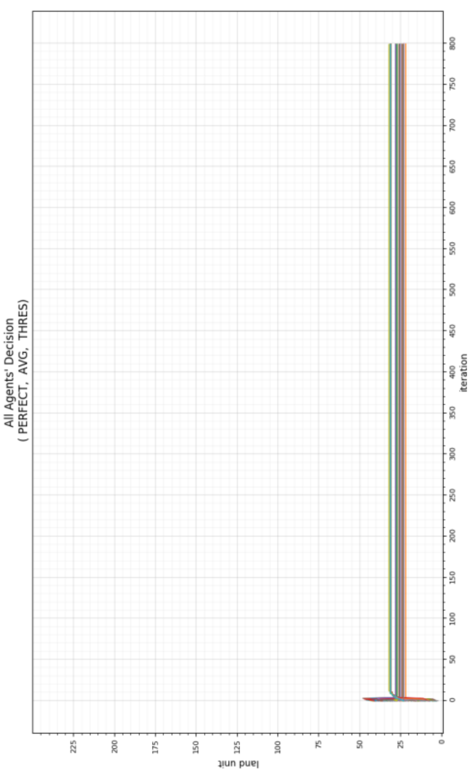
iteration
land unit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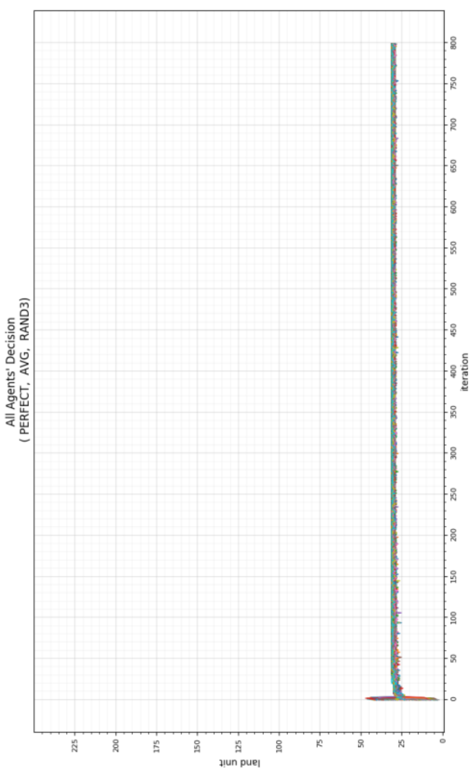
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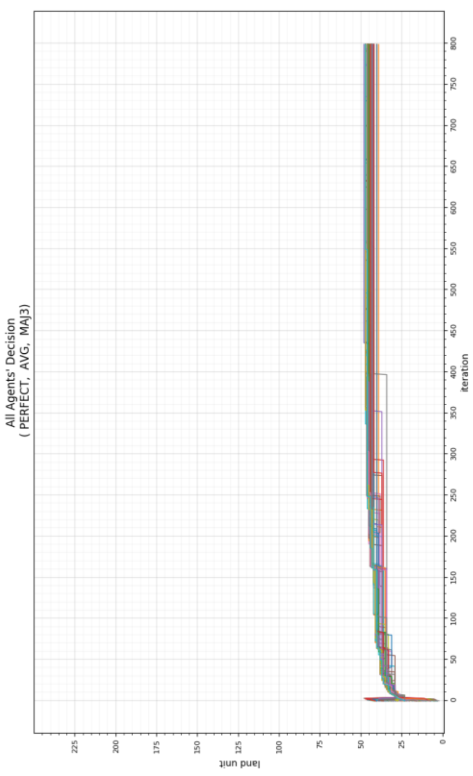
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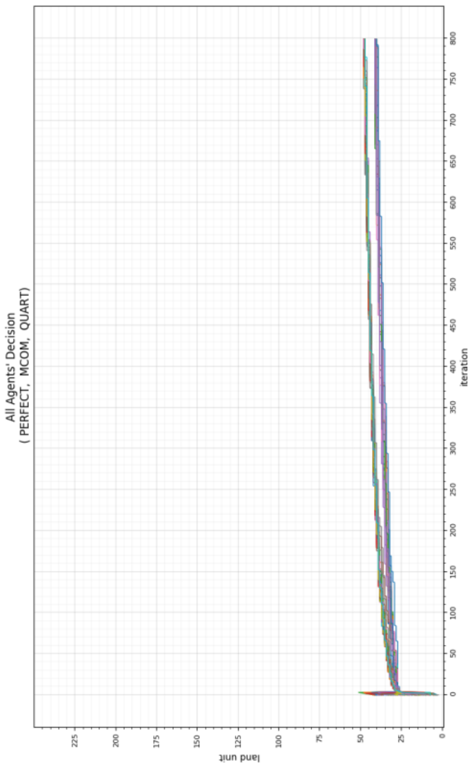
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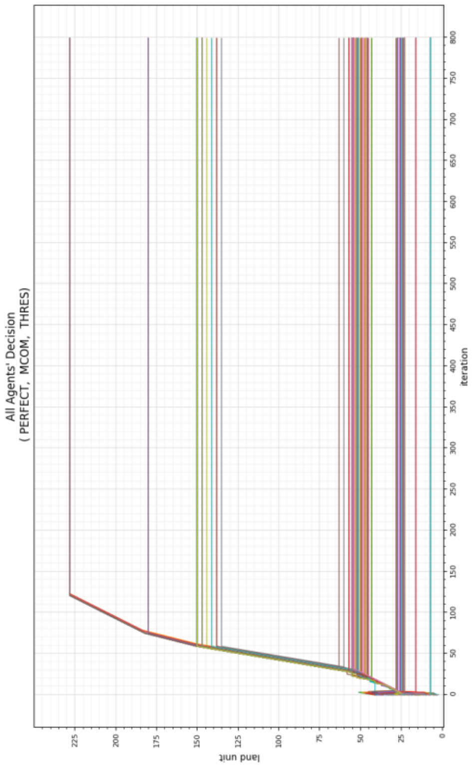
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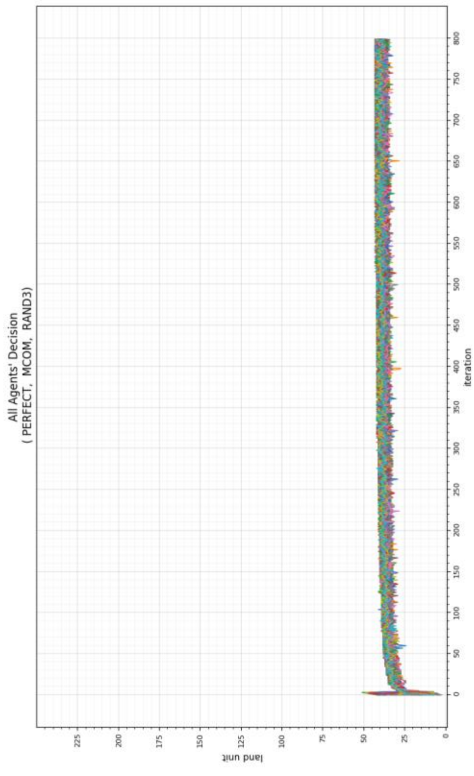
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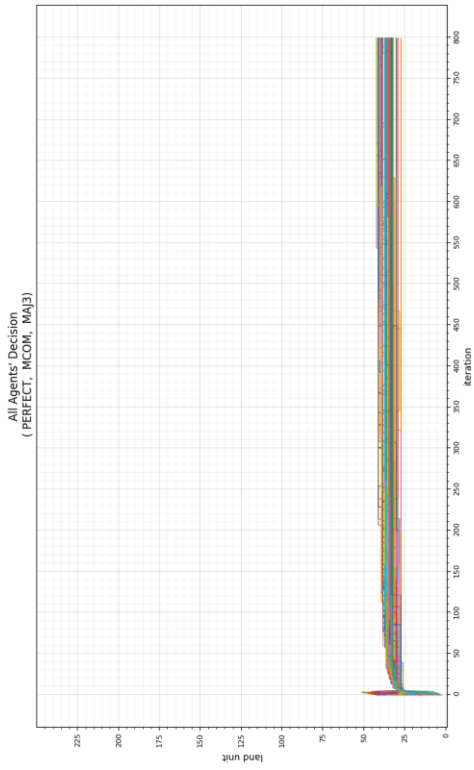
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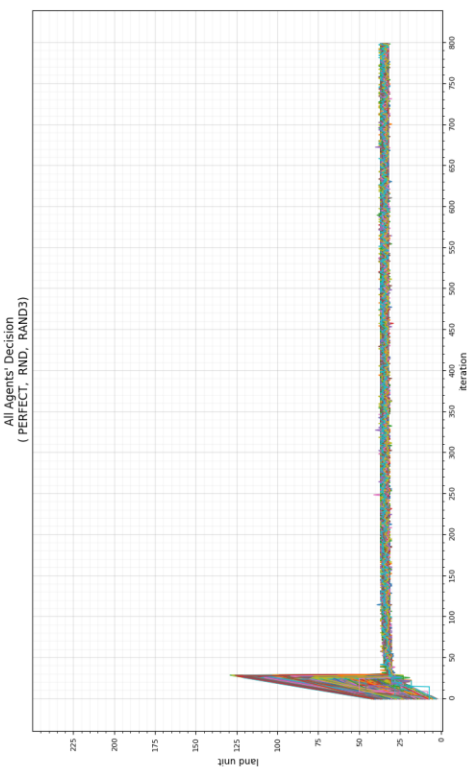
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land unit
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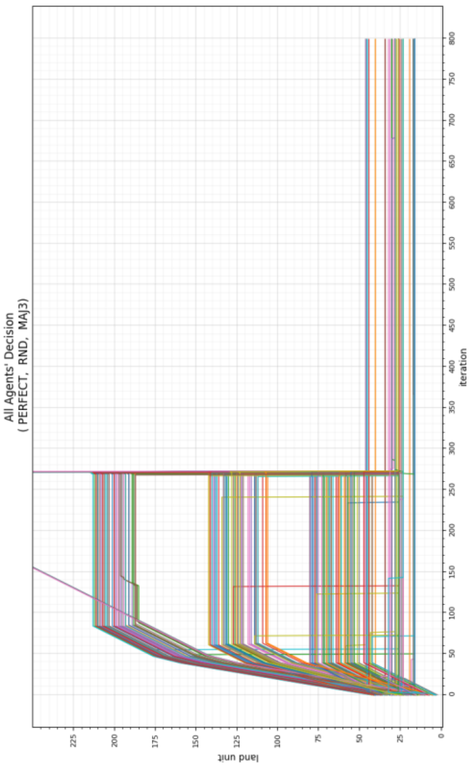
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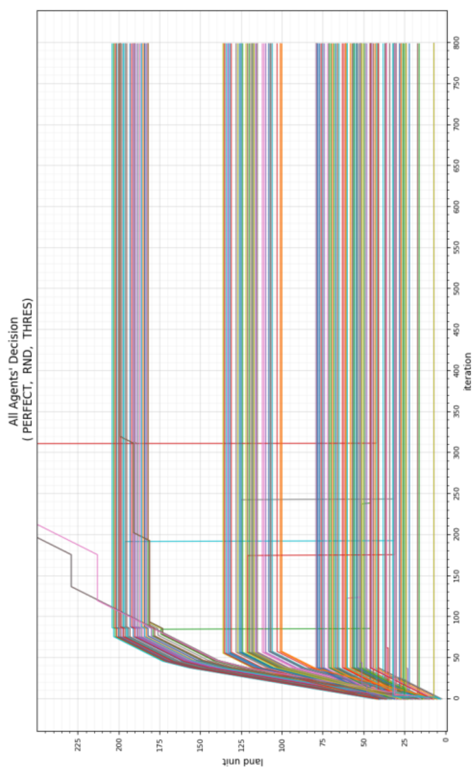
land unit
iteration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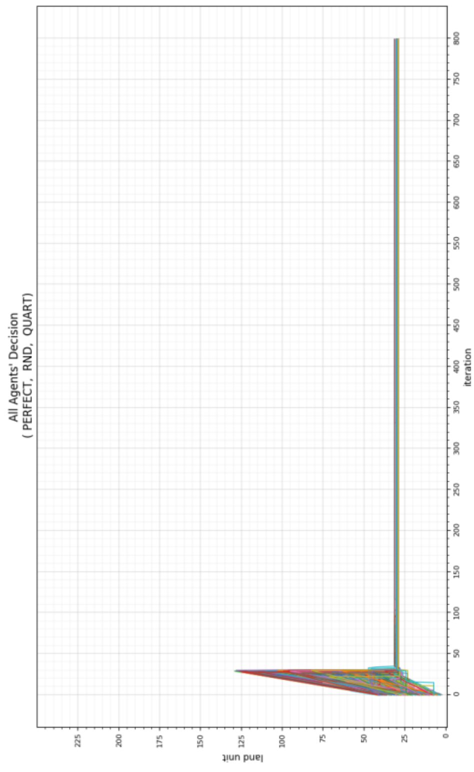
land unit
iteration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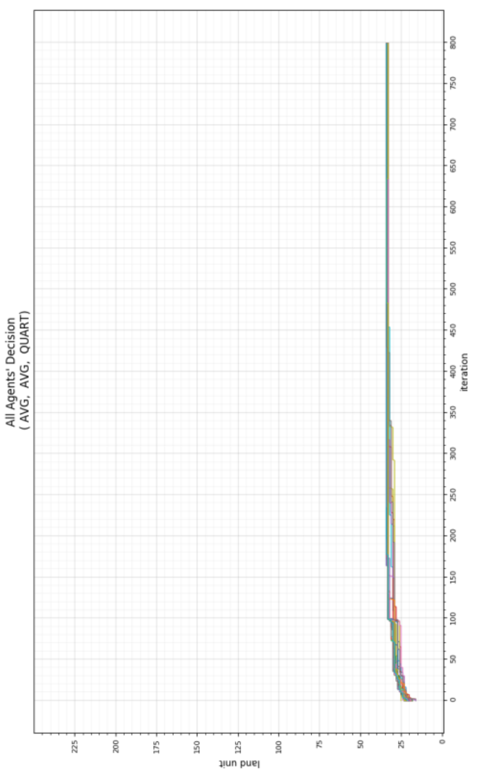
land unit
iteration

APPENDIX B
Norm Emergence for All Strategies in The Greedy Dominant Society


All Agents' Decision
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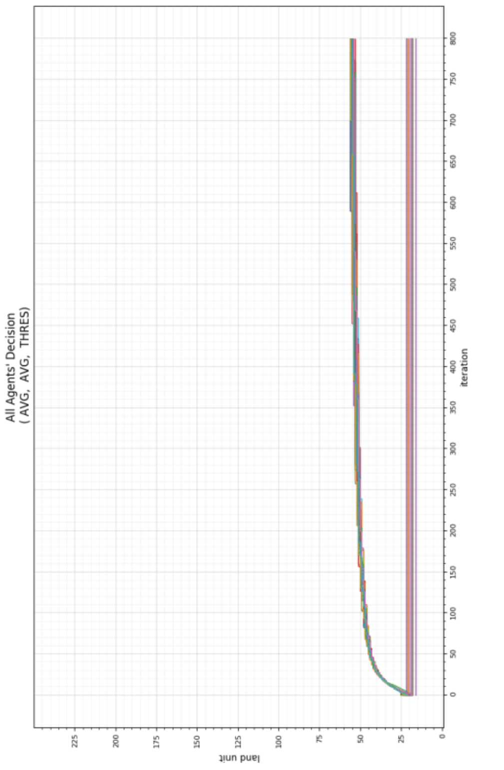
iteration
land unit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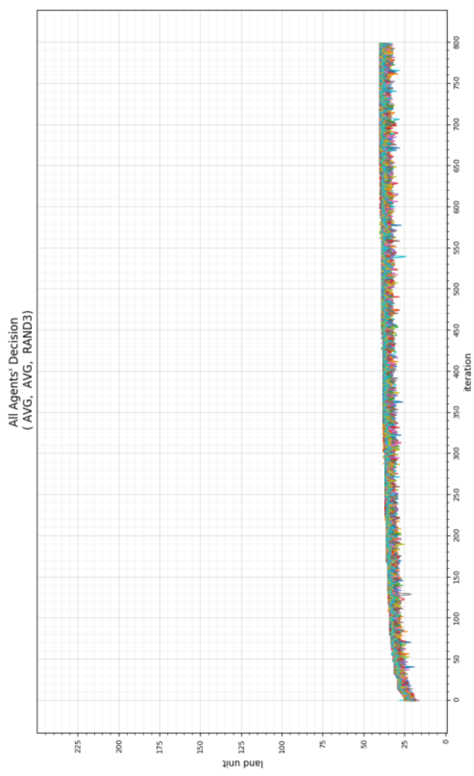
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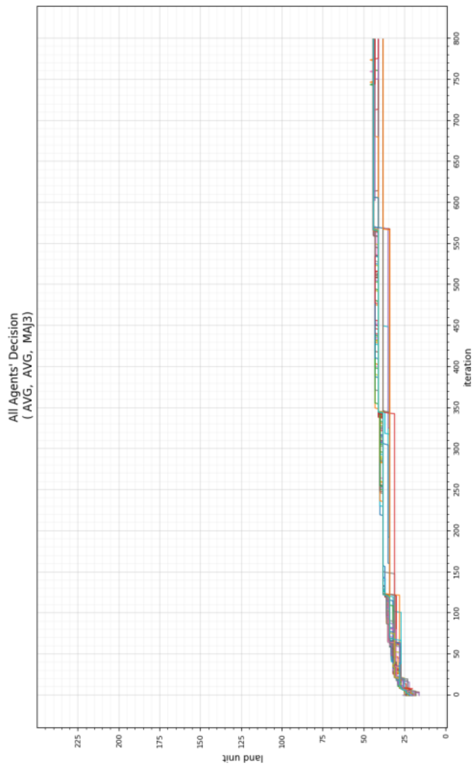
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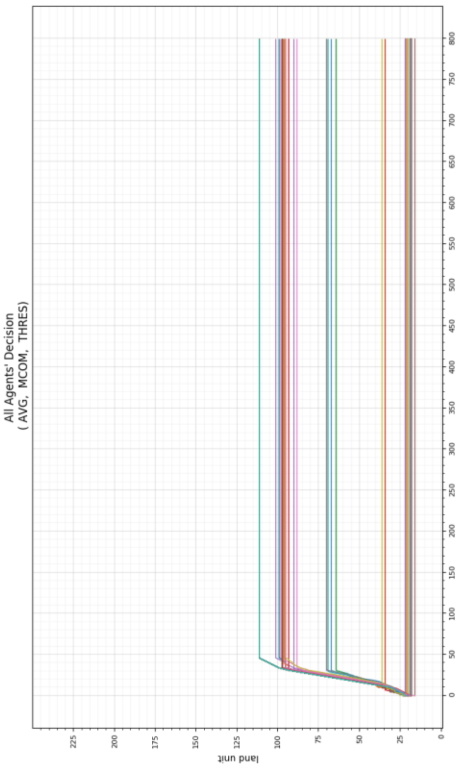
iteration
land unit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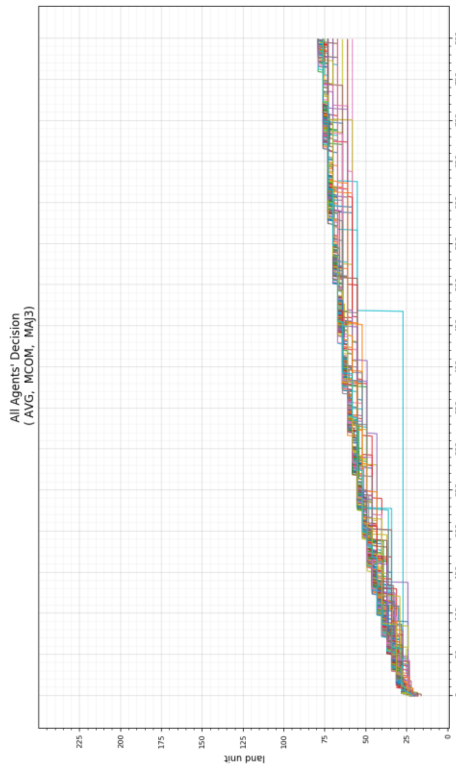
iteration
land unit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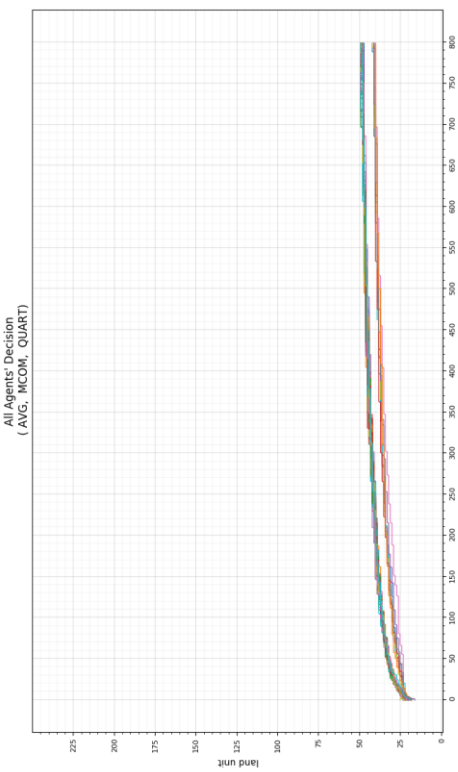
iteration
land unit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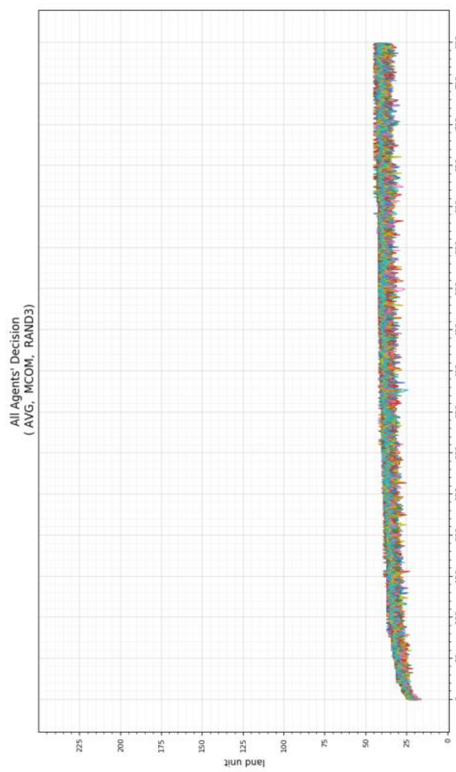
iteration
land unit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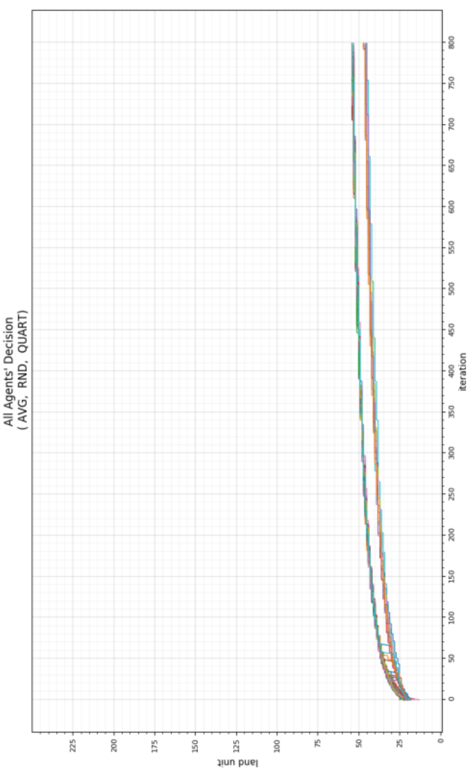
iteration
land unit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iteration
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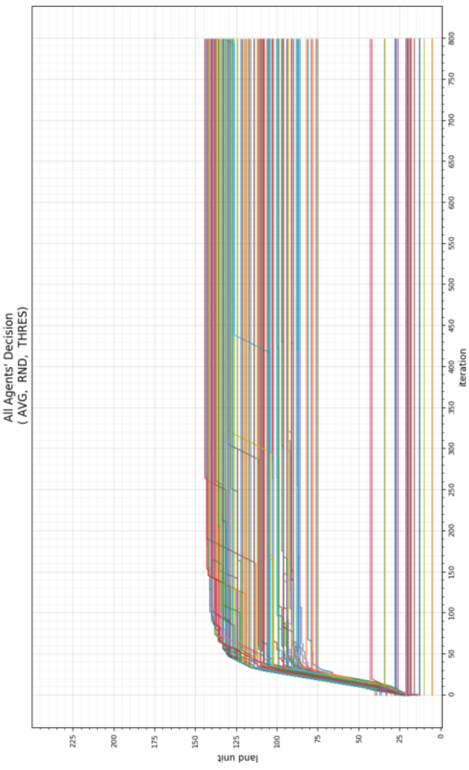
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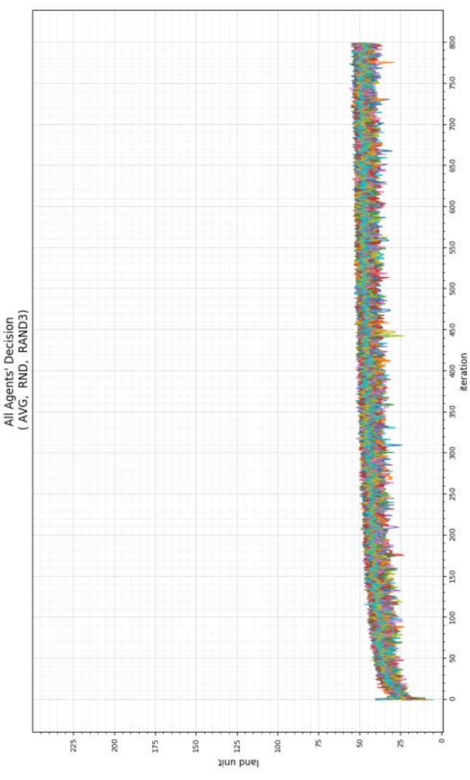
iteration
land unit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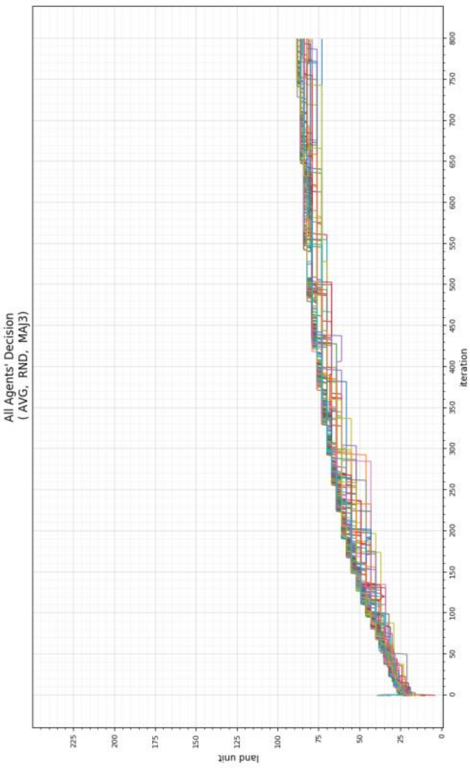
iteration
land unit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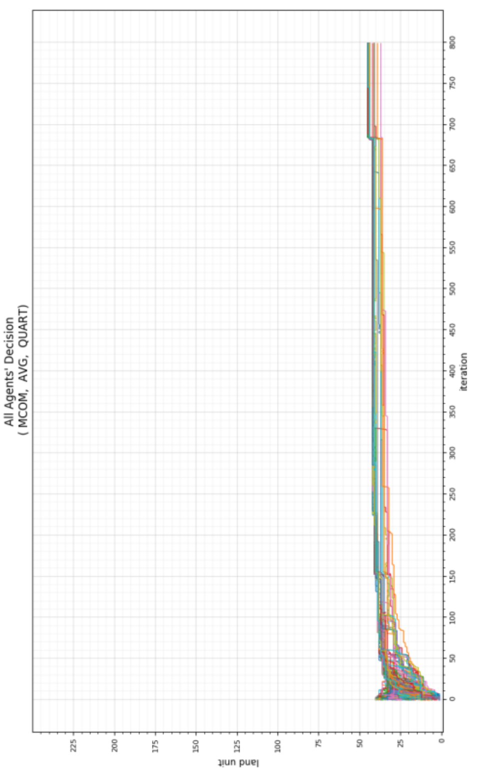
iteration
land unit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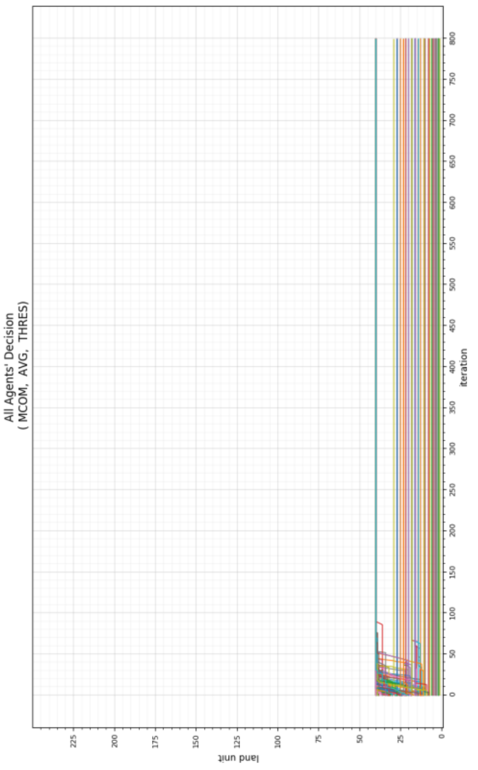
iteration
land unit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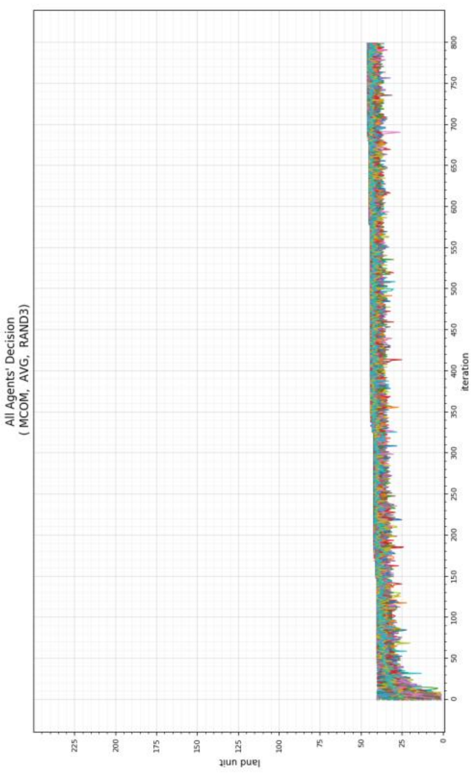
iteration
land unit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iteration
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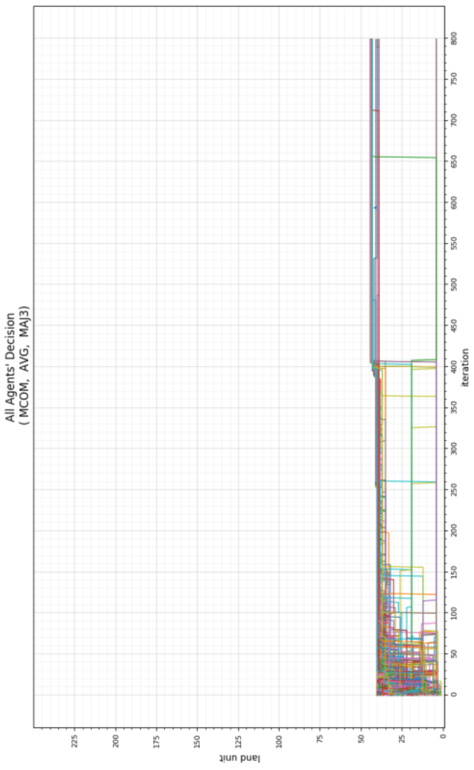
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iteration
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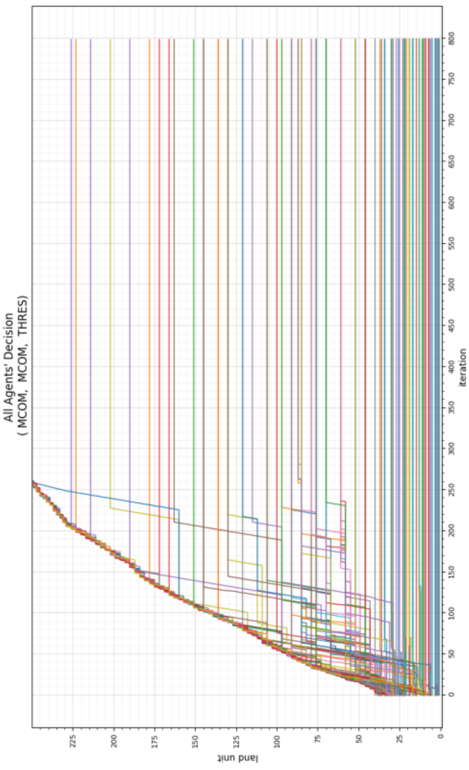
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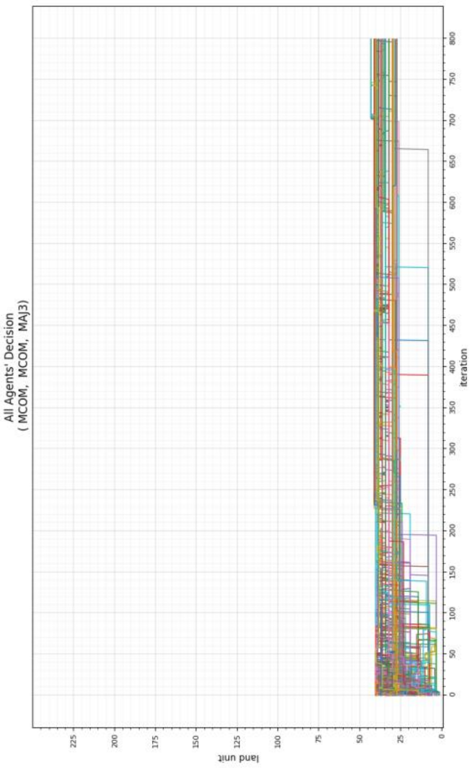
iteration
land unit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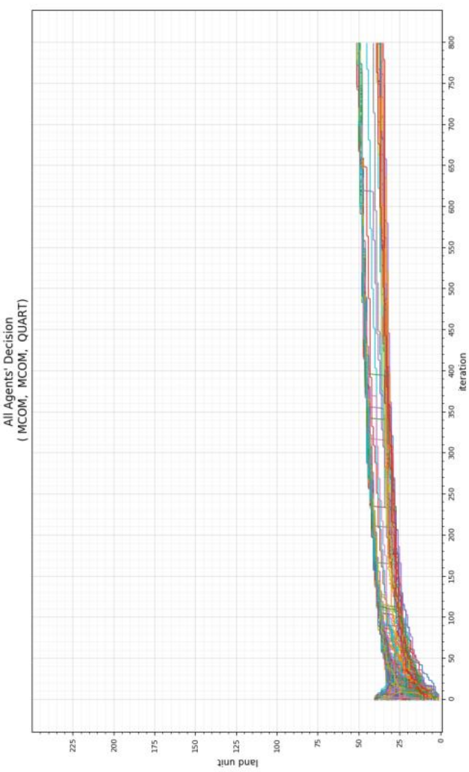
iteration
land unit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iteration
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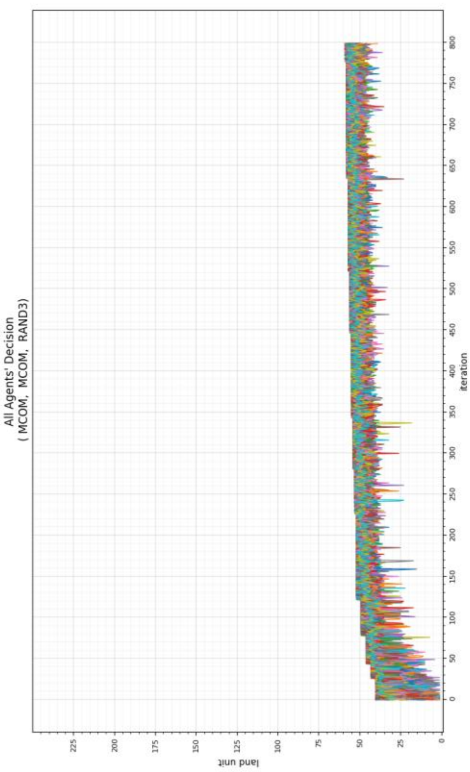
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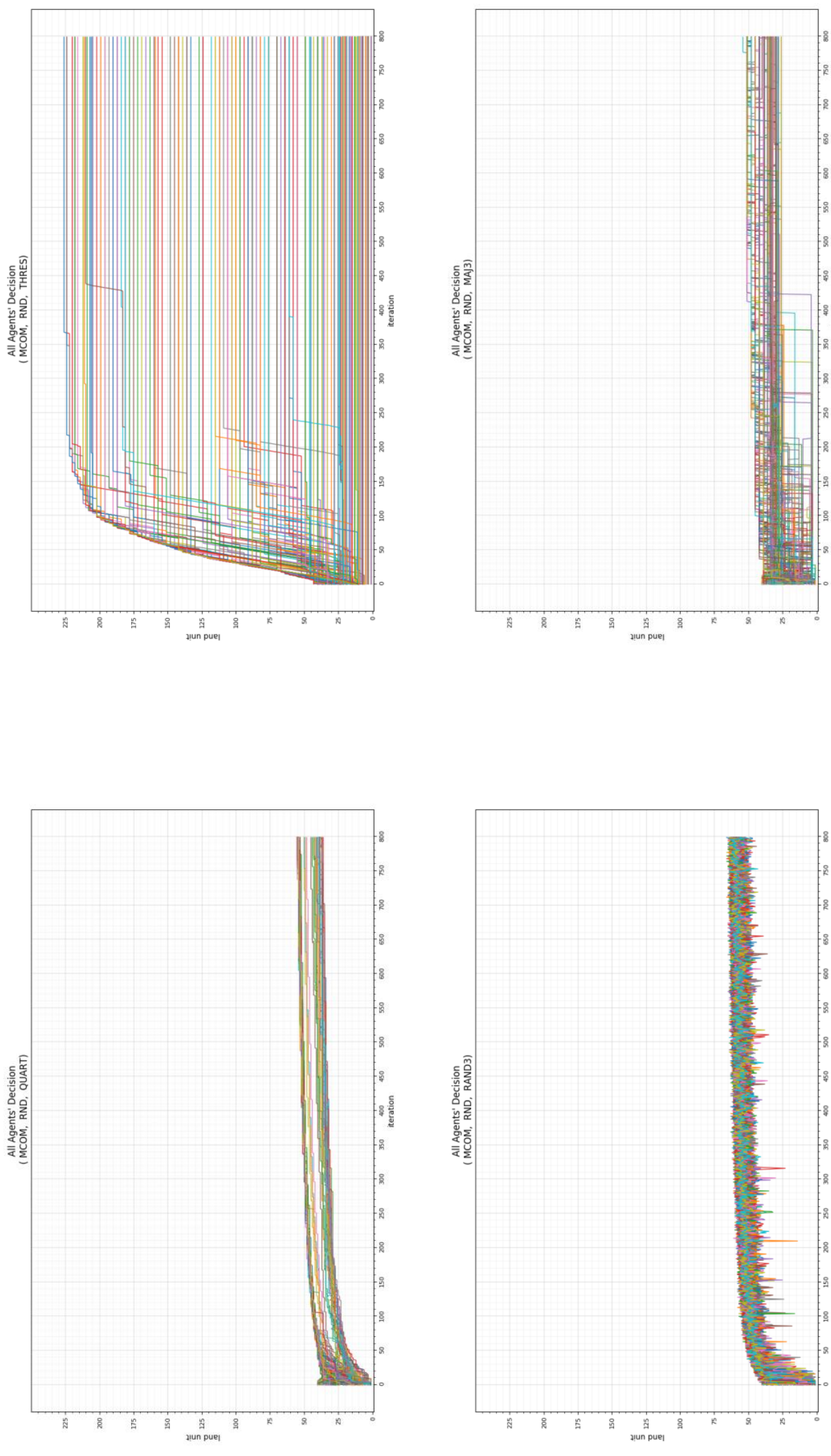
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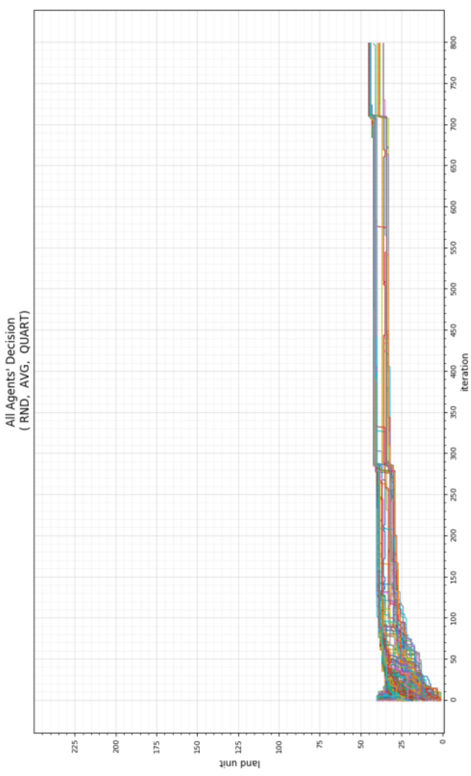
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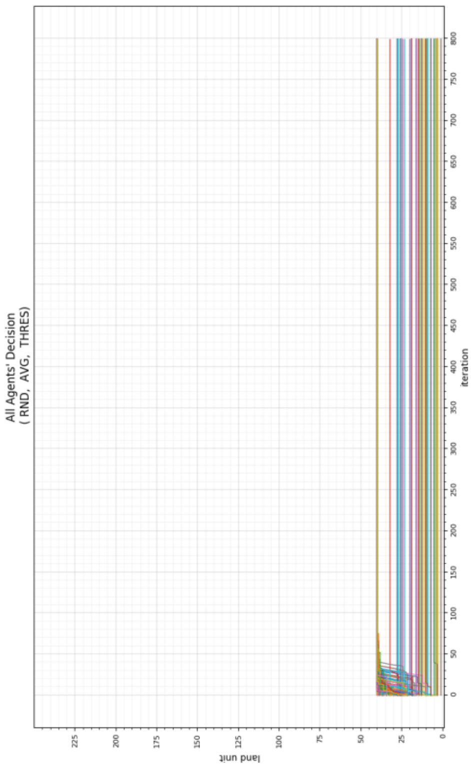
land unit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iteration
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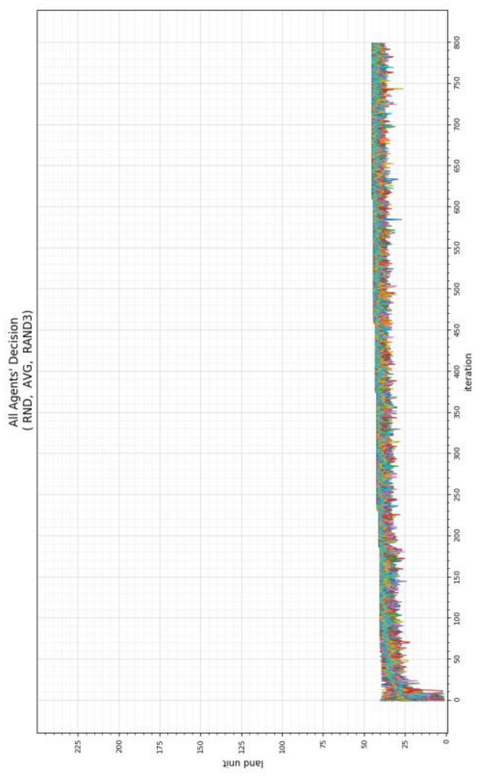
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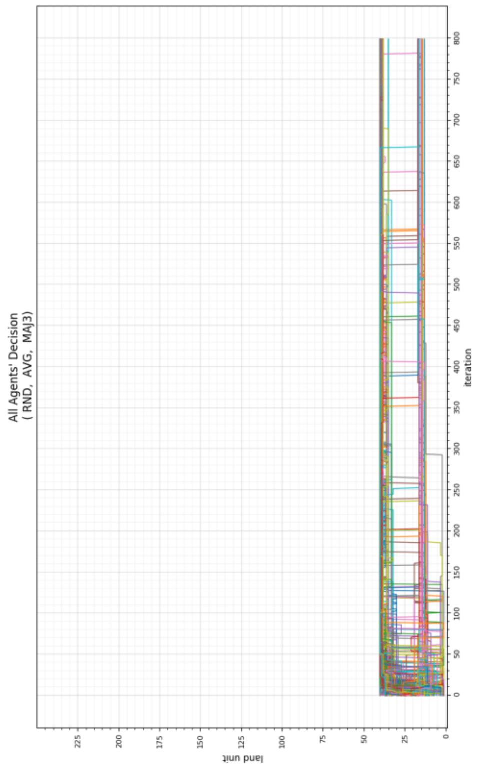
iteration
land unit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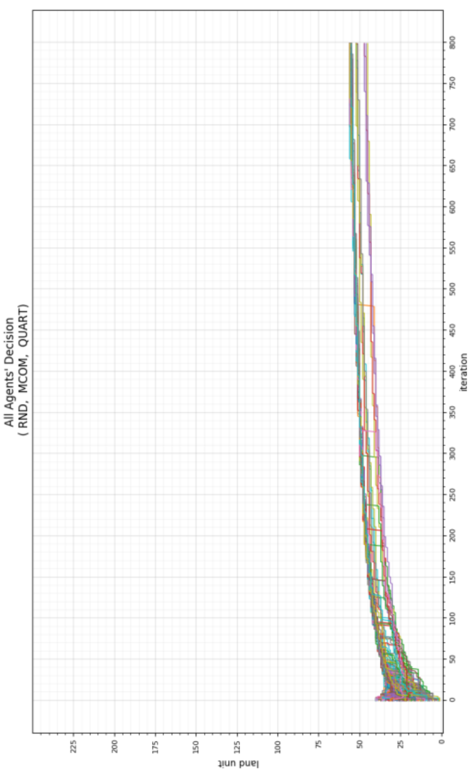
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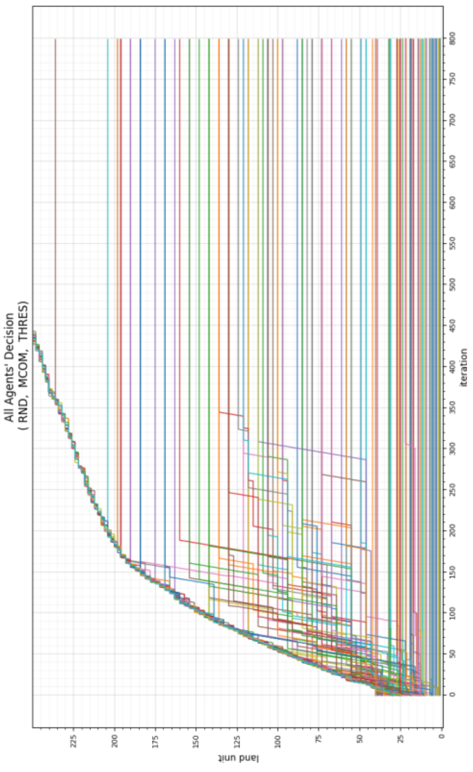
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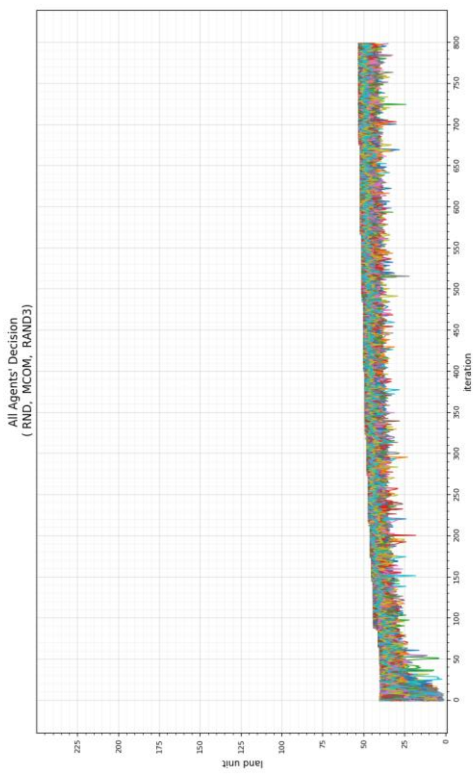
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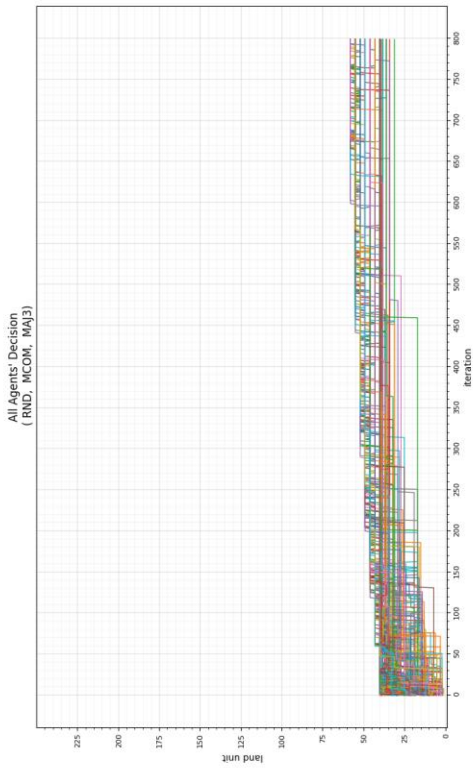
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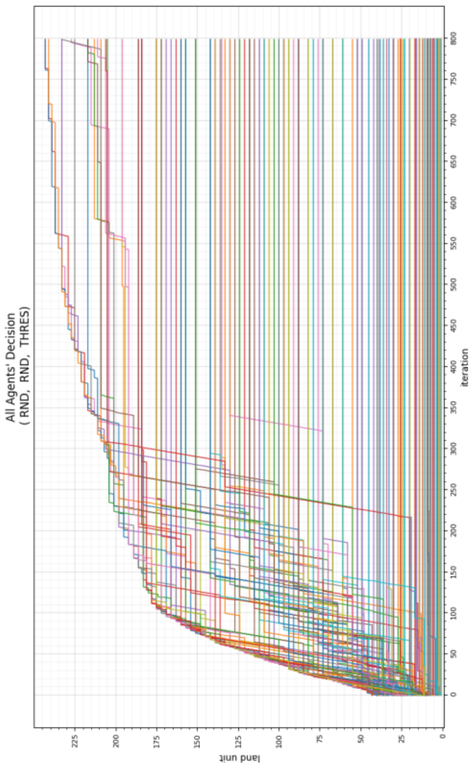
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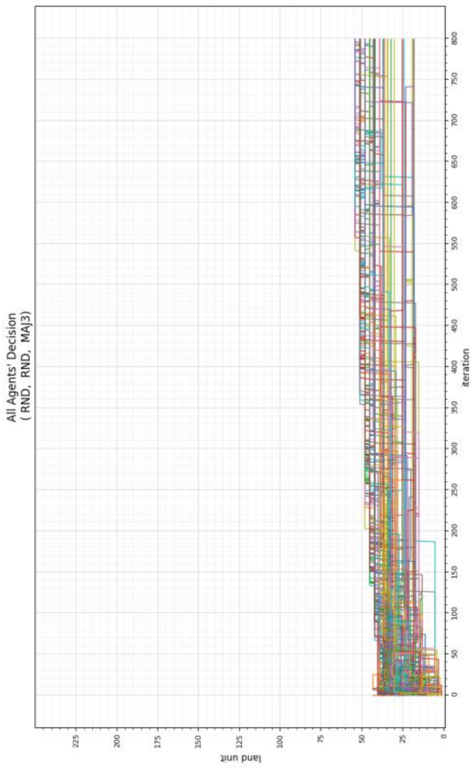
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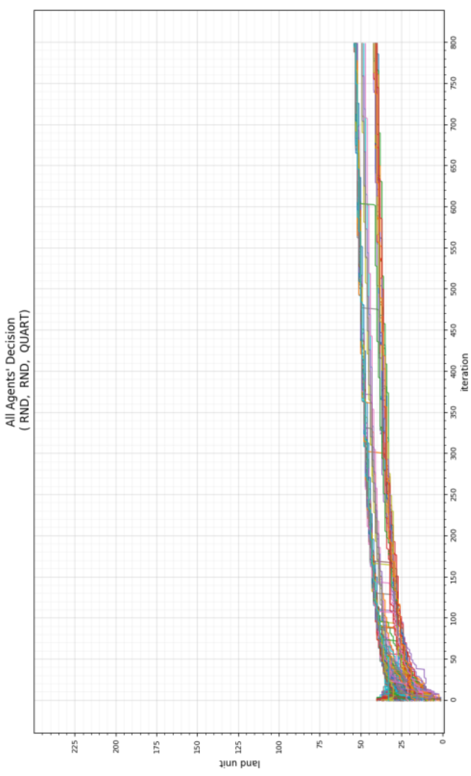
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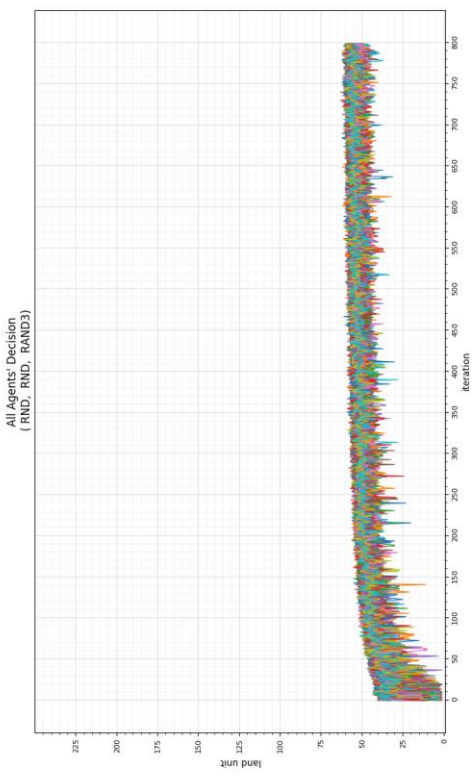
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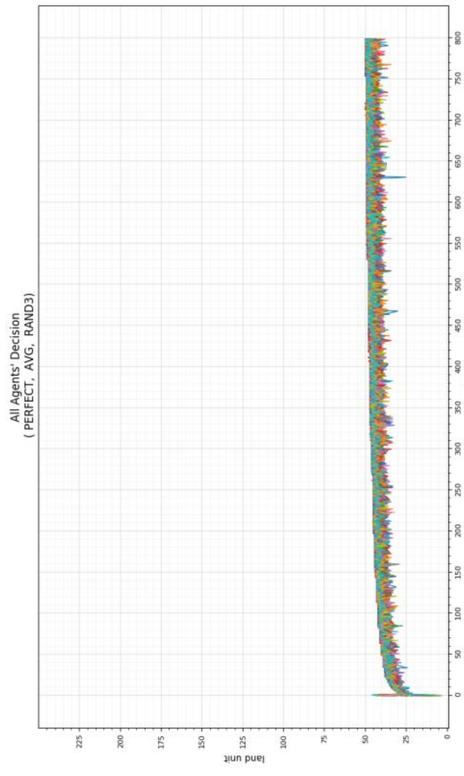
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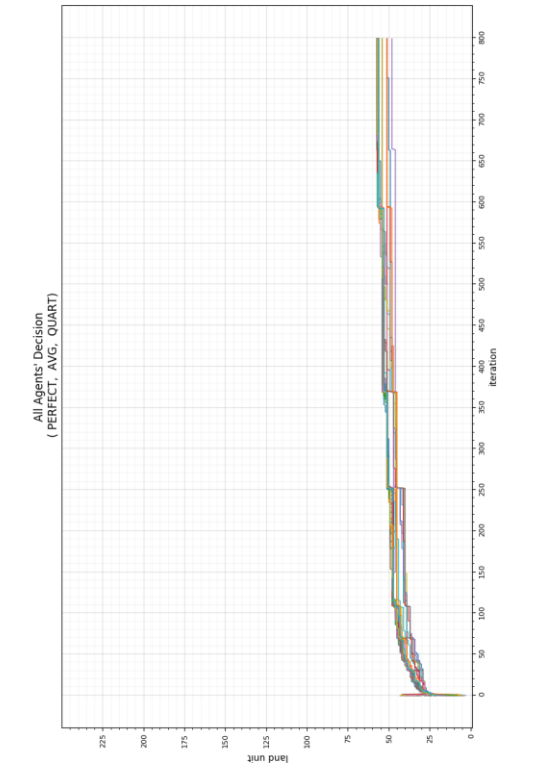
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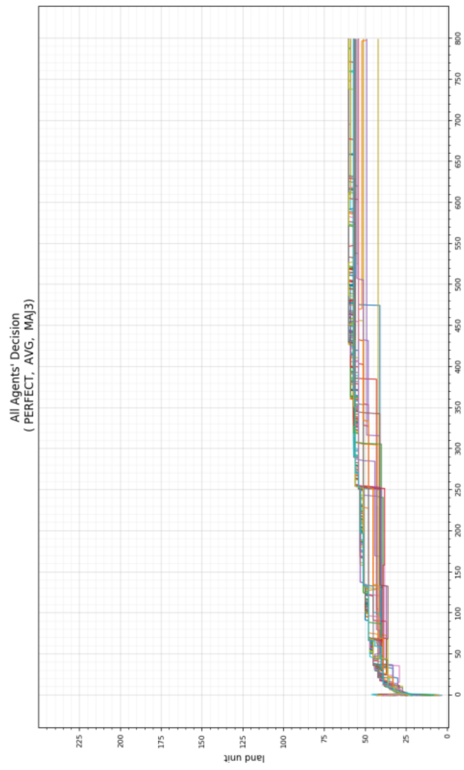
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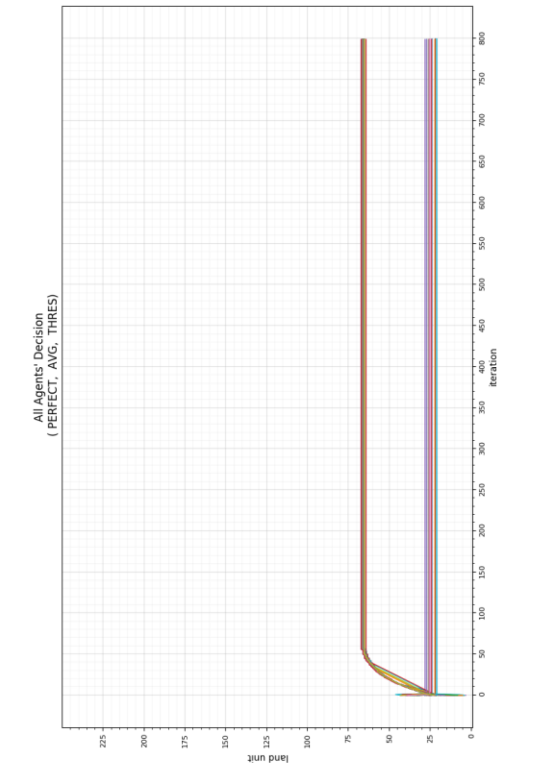
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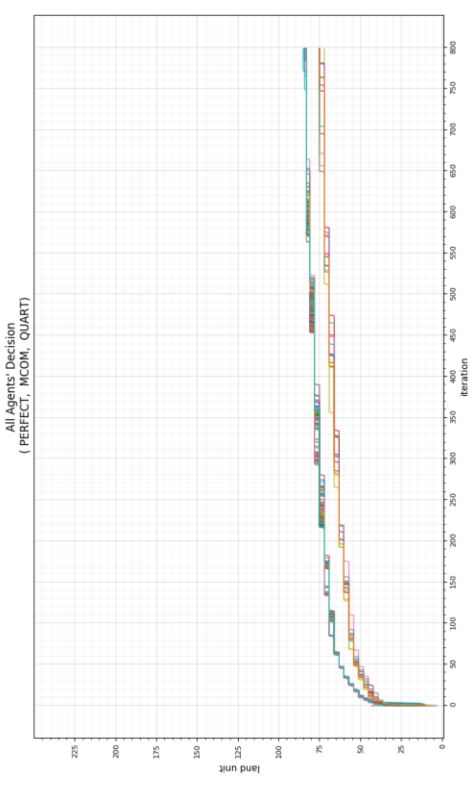
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(PERFECT, MCOM, QUART)
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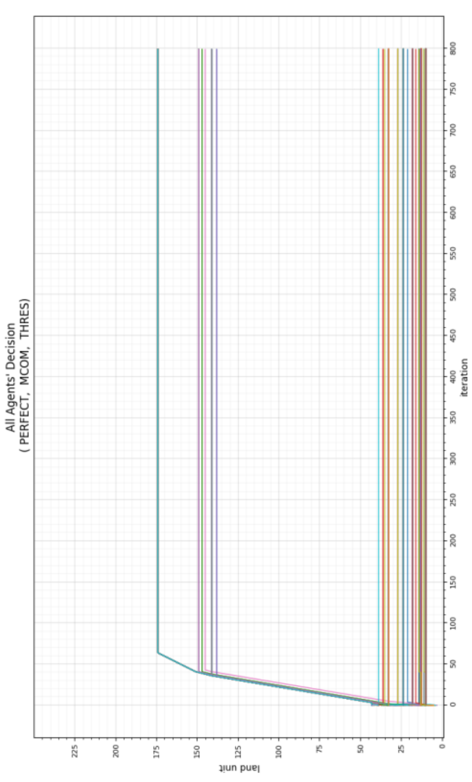
iteration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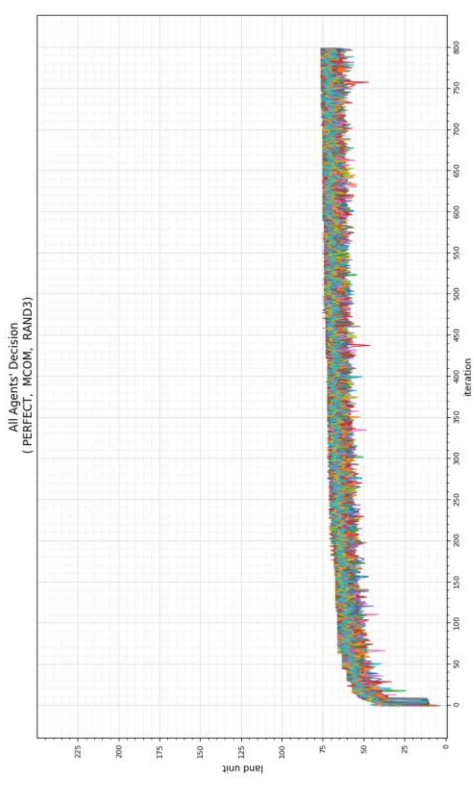
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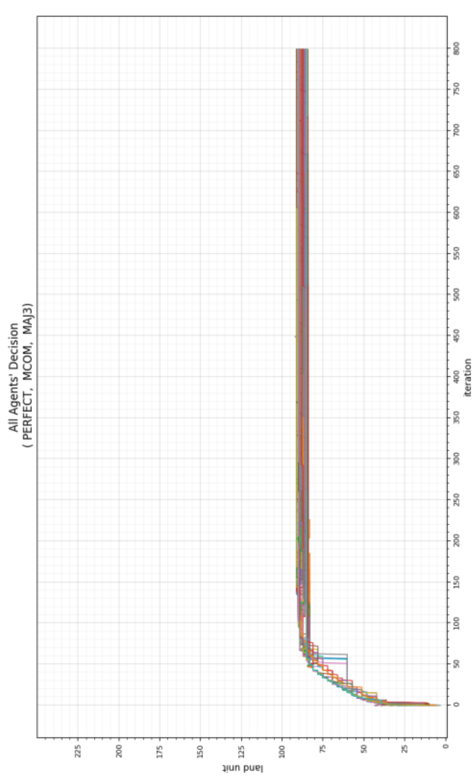
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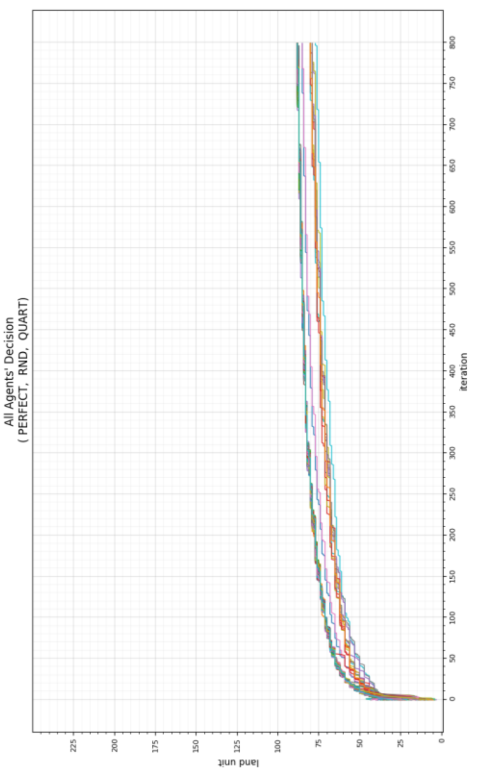
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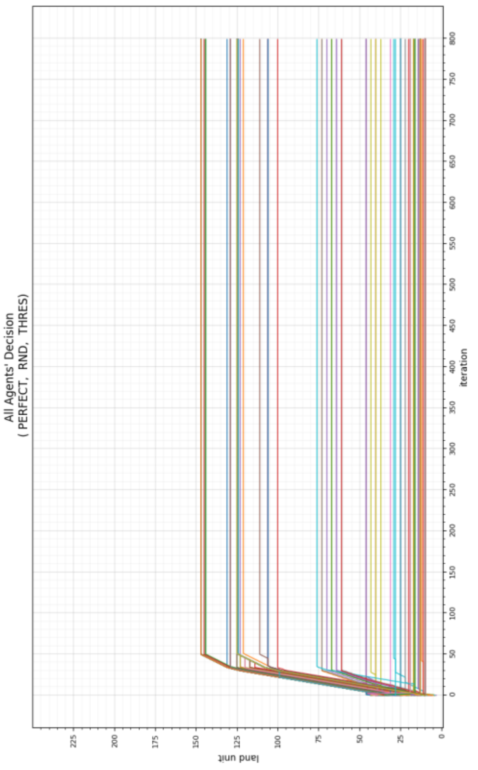
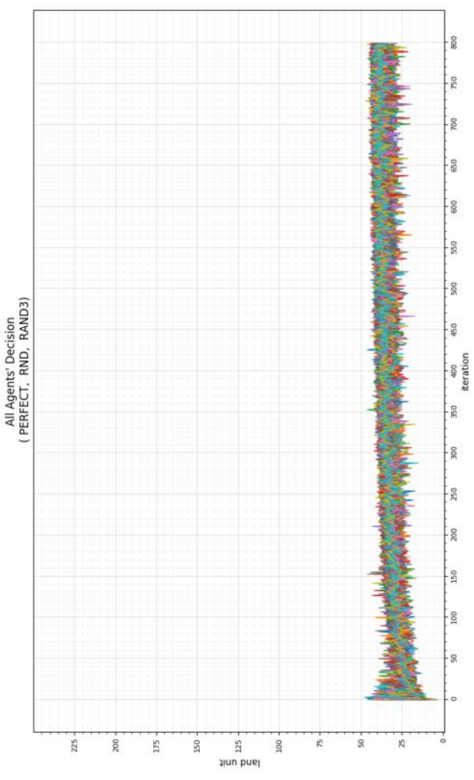
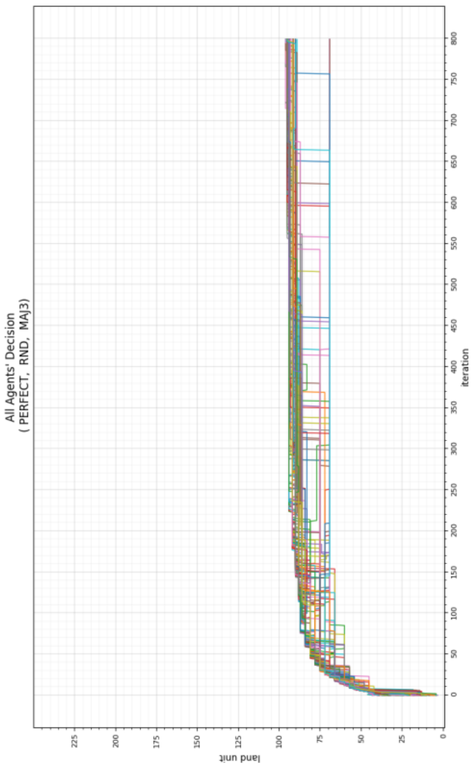
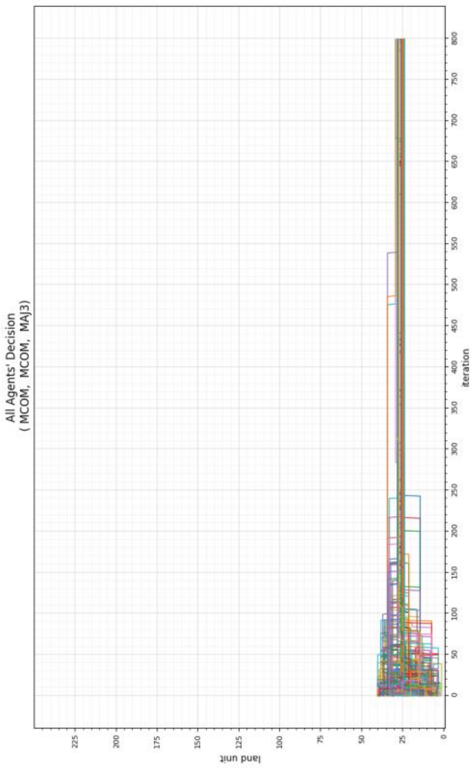

All Agents' Decision
(PERFECT, RND, THRES)
iteration
land unit

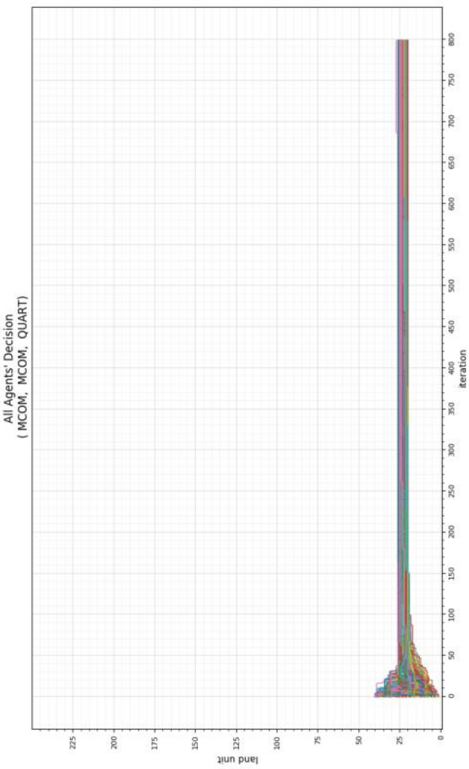

All Agents' Decision
(PERFECT, RND, RAND3)
iteration
land unit

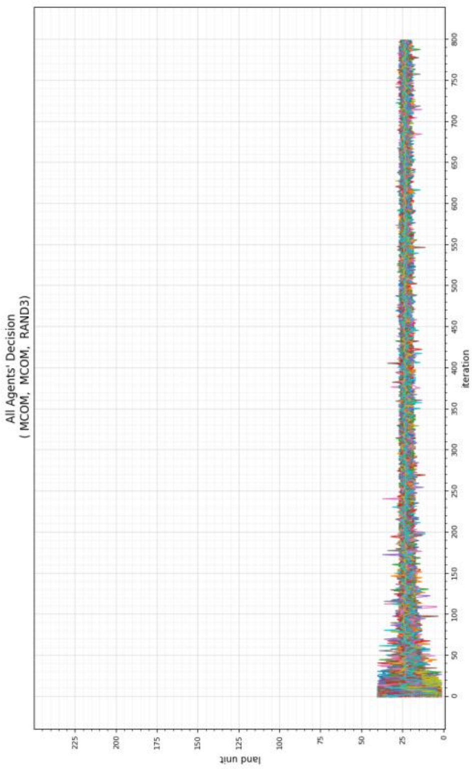

All Agents' Decision
(PERFECT, RND, MAJ3)
iteration
land unit

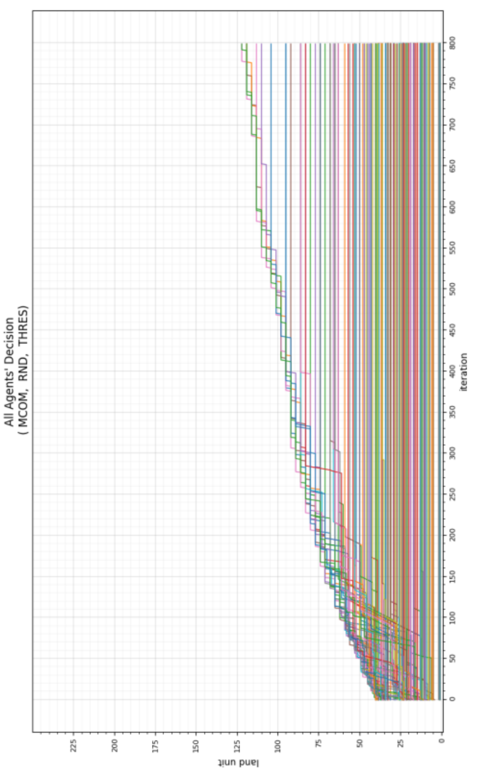
APPENDIX C
Norm Emergence for All Strategies in The Modest Dominant Society

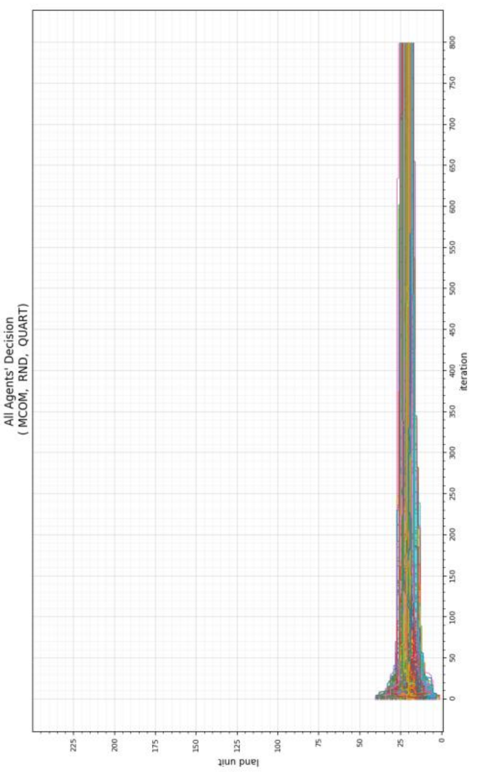

All Agents' Decision
(MCOM, MCOM, THRES)
iteration
land unit

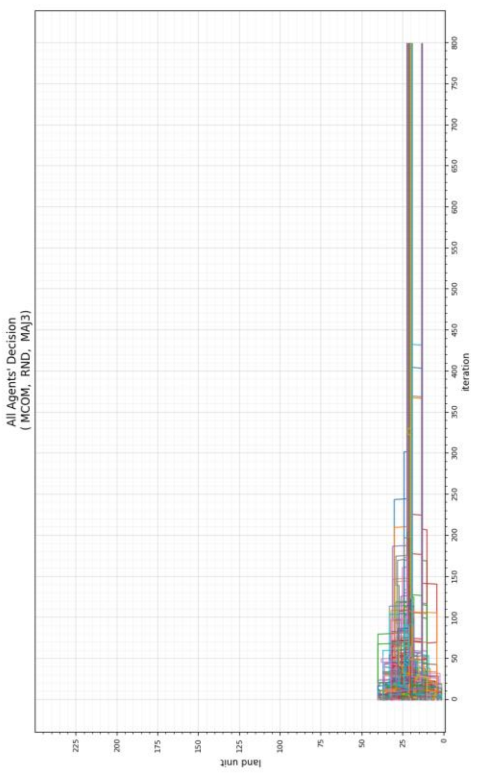

All Agents' Decision
(MCOM, MCOM, MAJ3)
iteration
land unit


All Agents' Decision
(MCOM, MCOM, QUART)
iteration
land unit


All Agents' Decision
(MCOM, MCOM, RAND3)
iteration
land unit


All Agents' Decision
(MCOM, RND, THRES)
iteration
land unit


All Agents' Decision
(MCOM, RND, QUART)
iteration
land unit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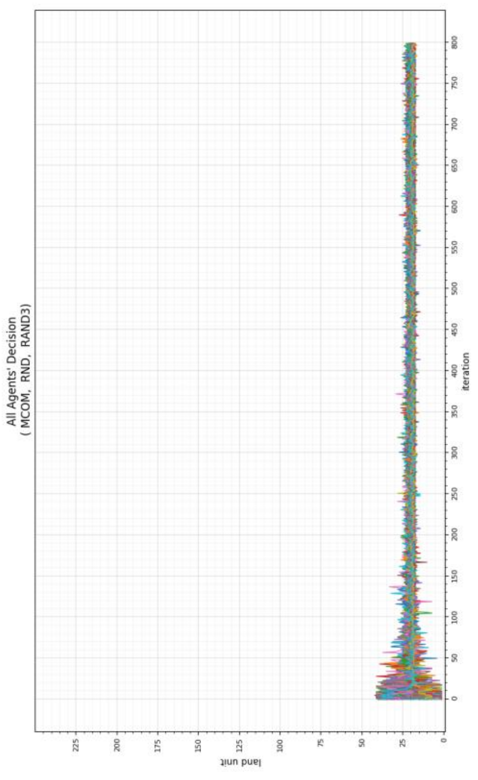
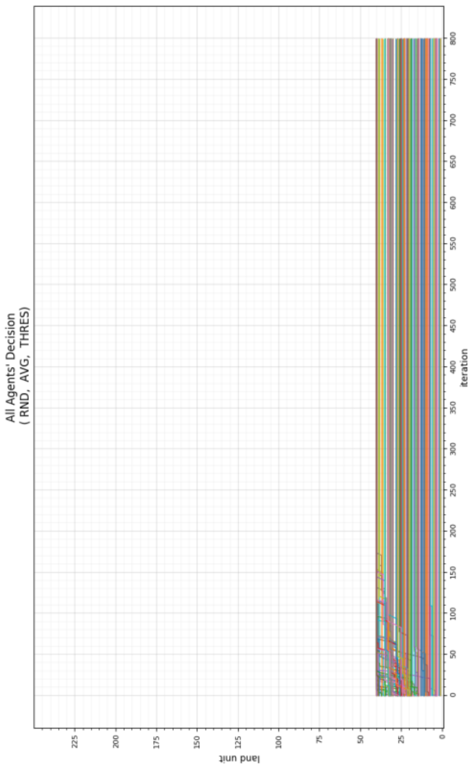
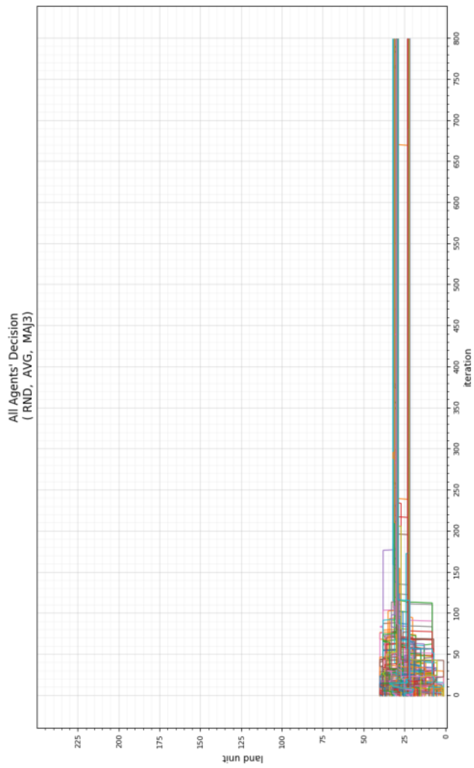
(MCOM, RND, MAJ3)
iteration
land unit


All Agents' Decision
(MCOM, RND, RAND3)
iteration
land unit


All Agents' Decision
(RND, AVG, THRES)
iteration
land unit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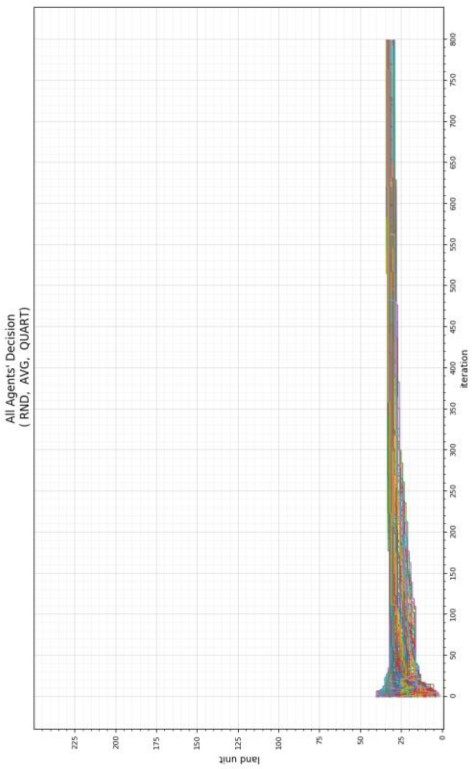
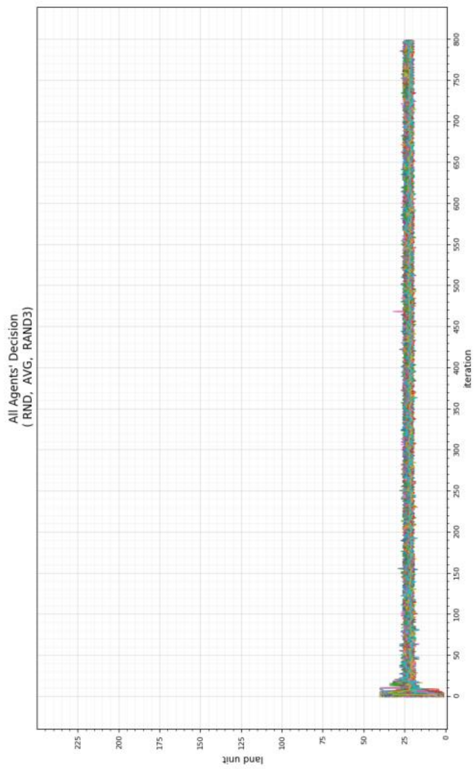
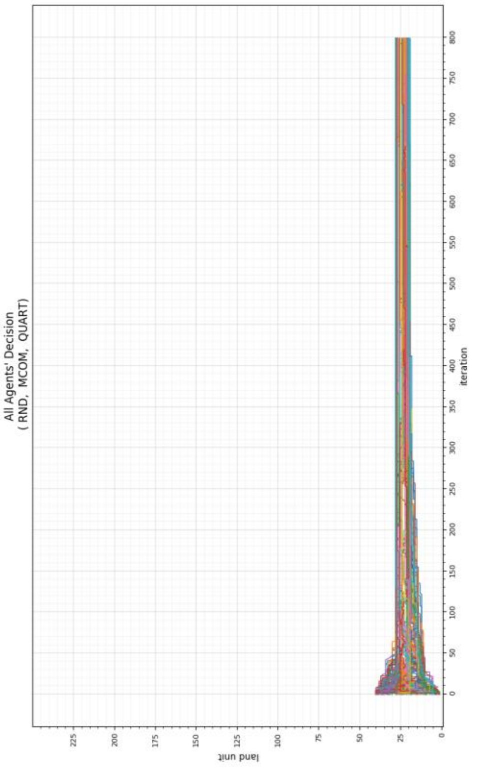
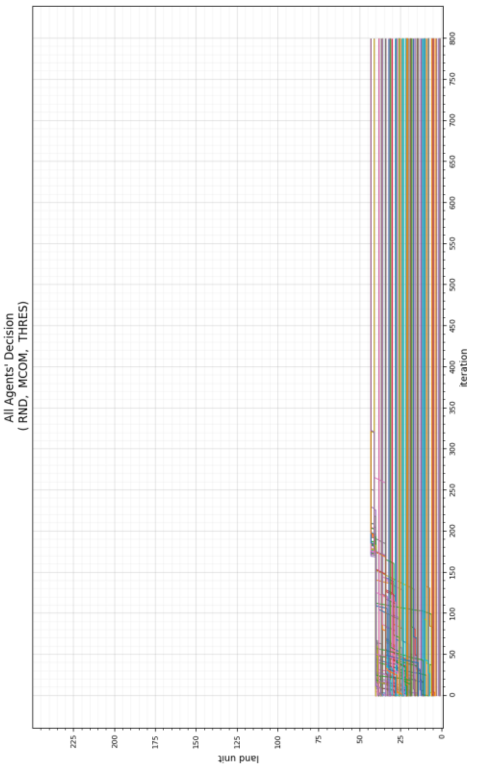
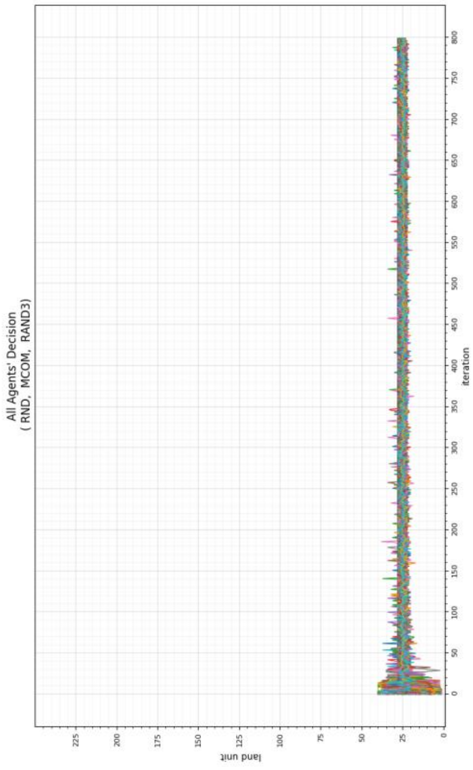
(RND, AVG, MAJ3)
iteration
land unit

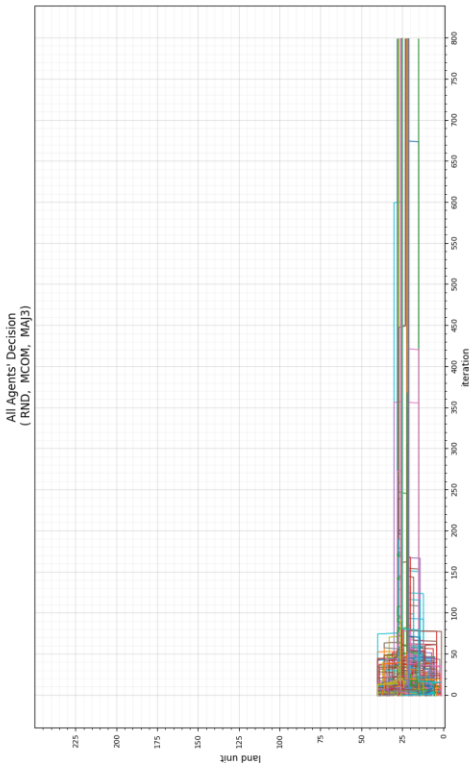

All Agents' Decision
(RND, AVG, QUART)
iteration
land unit

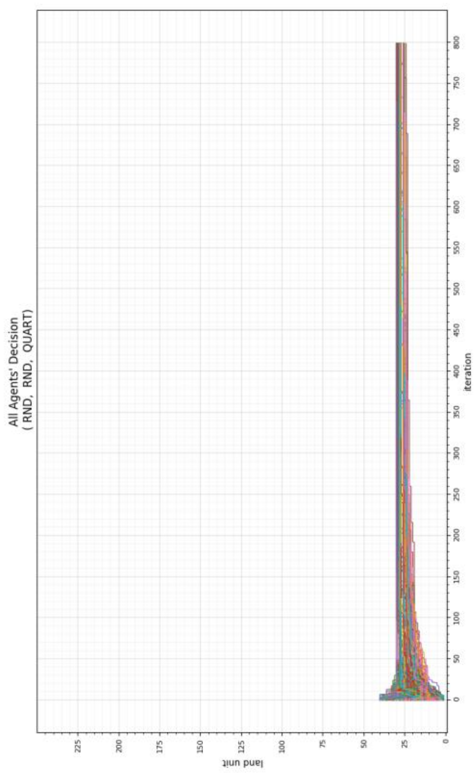

All Agents' Decision
(RND, AVG, RAND3)
iteration
land unit


All Agents' Decision
(RND, MCOM, QUART)
land unit
iteration


All Agents' Decision
(RND, MCOM, THRES)
land unit
iteration


All Agents' Decision
(RND, MCOM, RAND3)
land unit
iteration


All Agents' Decision
(RND, MCOM, MAJ3)
land unit
iteration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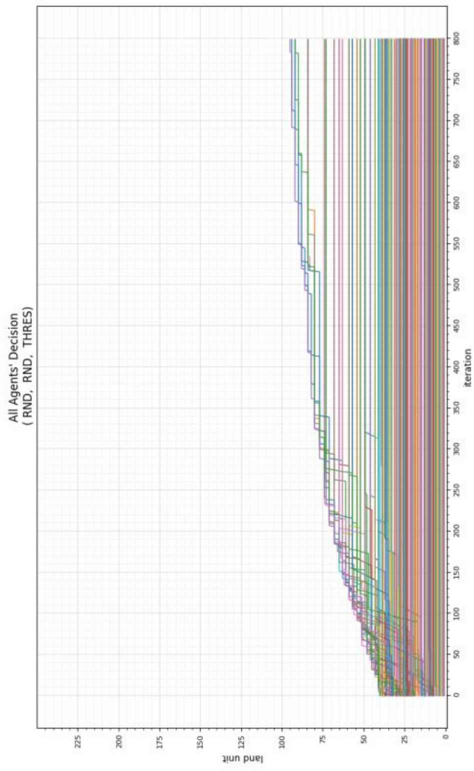
(RND, RND, QUART)
land unit
iteration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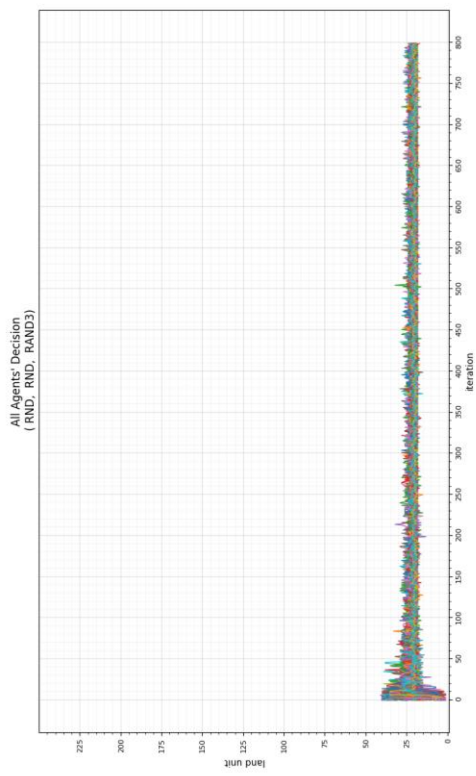
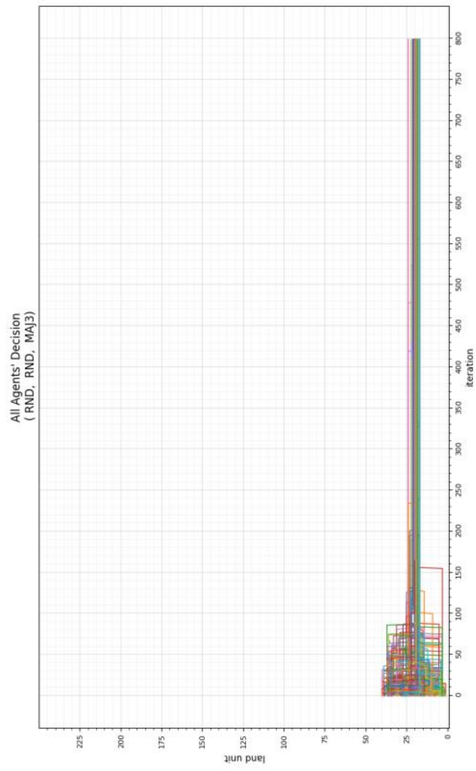
(RND, RND, THRES)
land unit
iteration


All Agents' Decision
(RND, RND, RAND3)
land unit
iteration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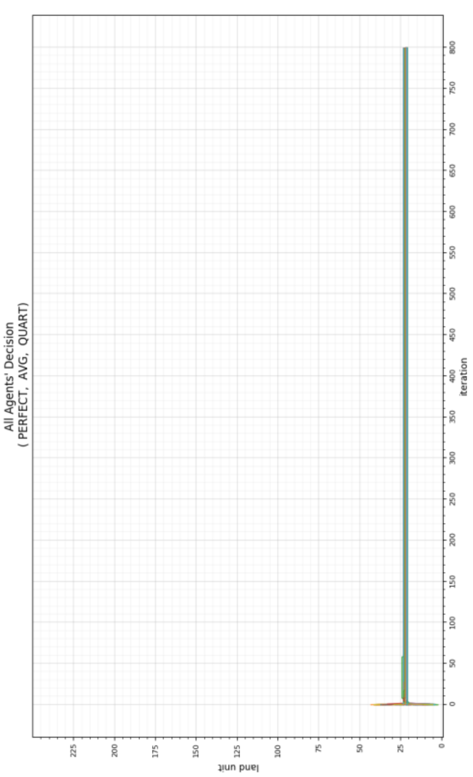
(RND, RND, MAJ3)
land unit
iteration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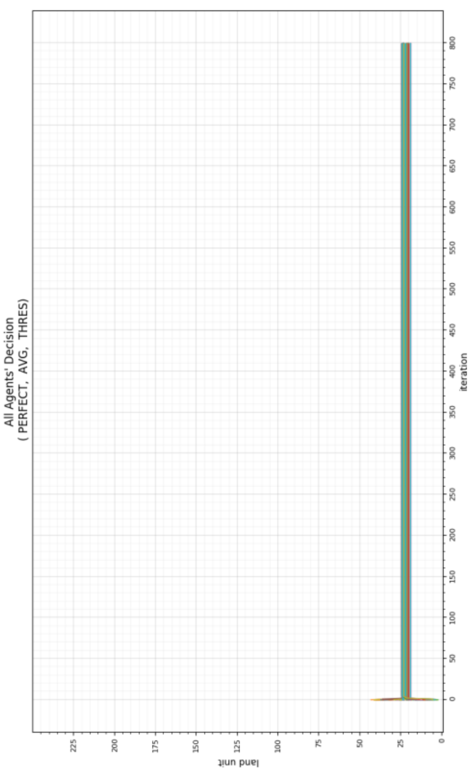
(PERFECT, AVG, QUART)
land unit
iteration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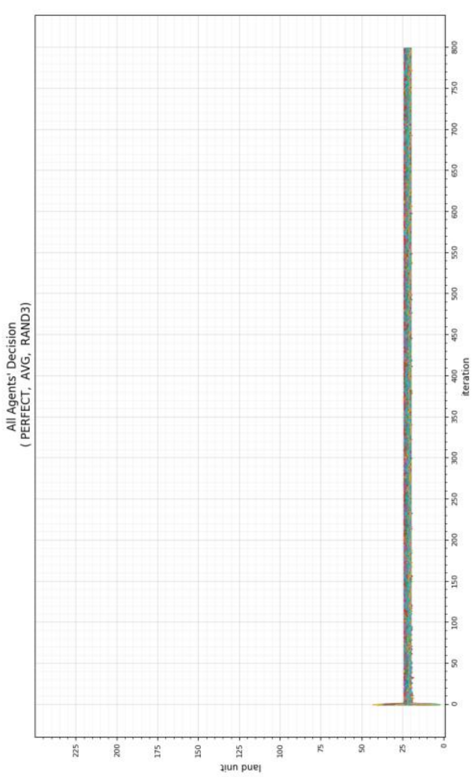
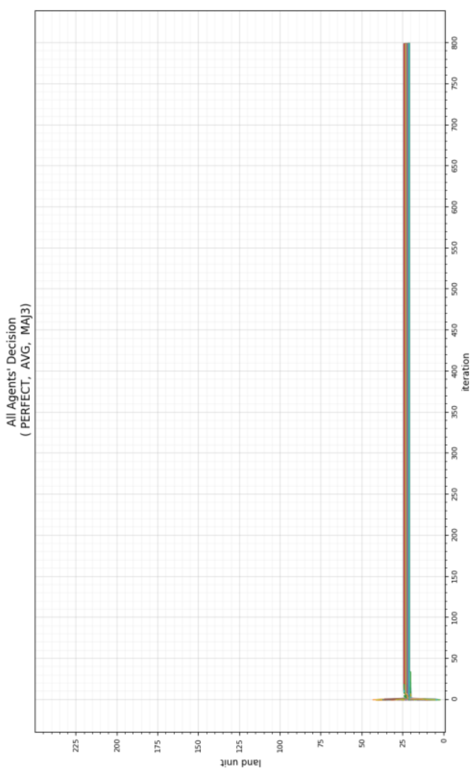
(PERFECT, AVG, THRES)
land unit
iteration


All Agents' Decision
(PERFECT, AVG, RAND3)
land unit
iteration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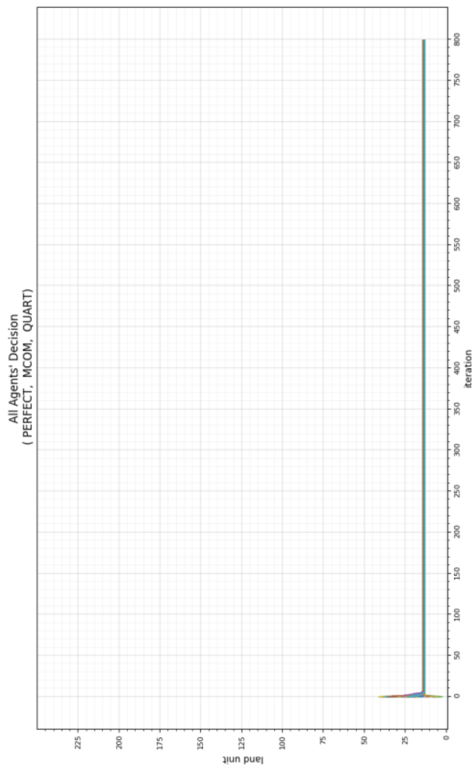
(PERFECT, AVG, MAJ3)
land unit
iteration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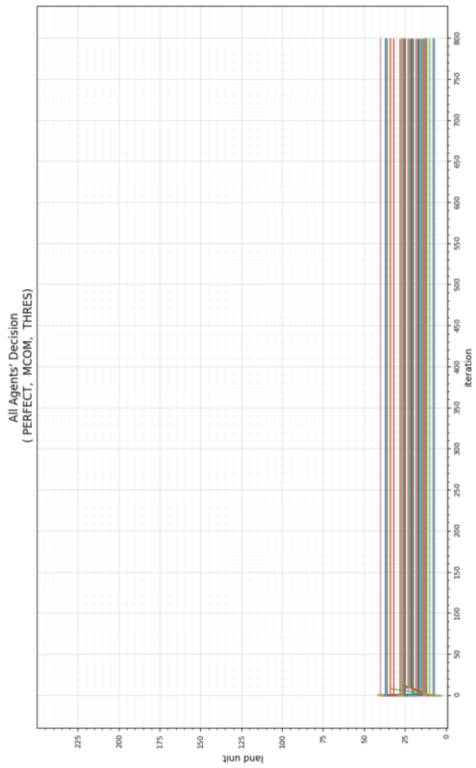
(PERFECT, MCOM, QUART)
land unit
iteration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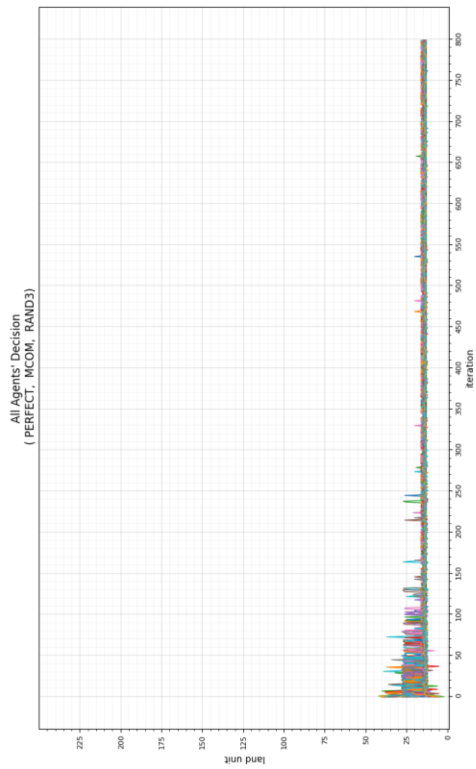
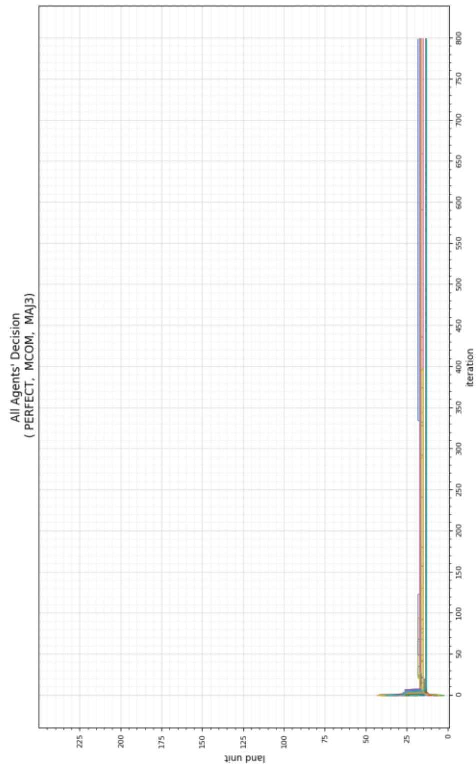
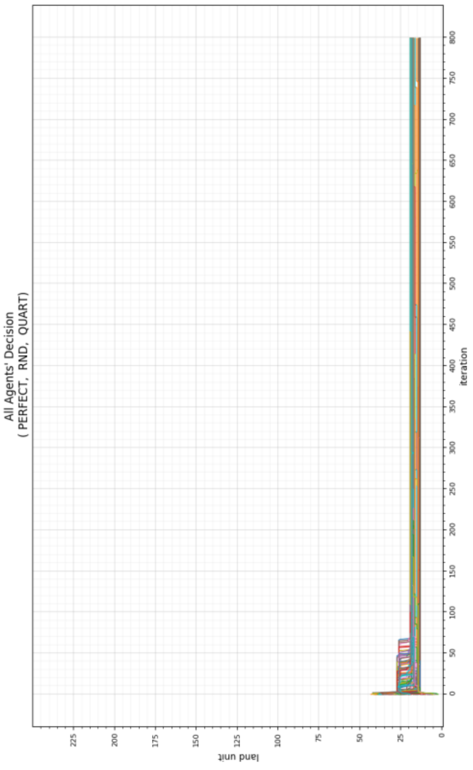
(PERFECT, MCOM, THRES)
land unit
iteration


All Agents' Decision
(PERFECT, MCOM, RAND3)
land unit
iteration


All Agents' Decision
(PERFECT, MCOM, MAJ3)
land unit
iteration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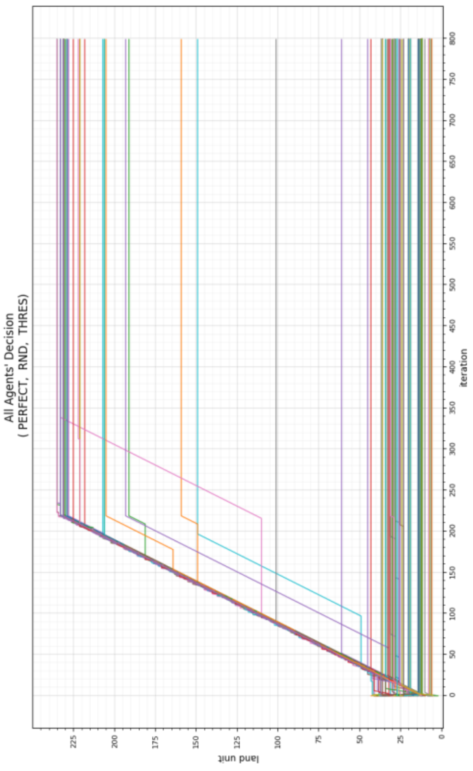
(PERFECT, RND, QUART)
land unit
iteration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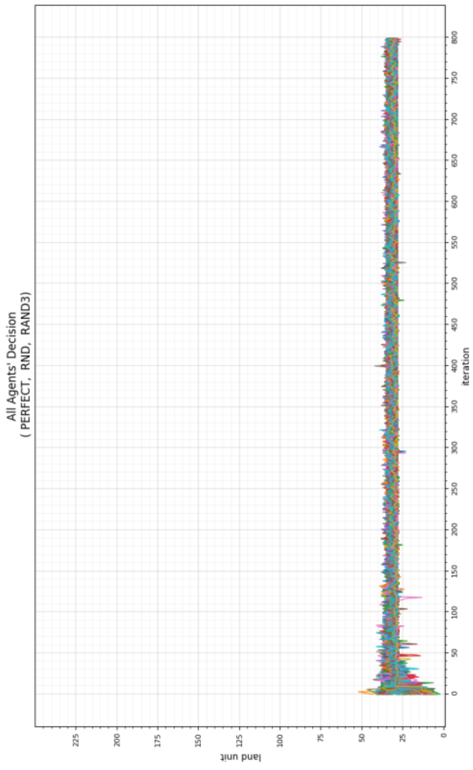
(PERFECT, RND, THRES)
land unit
iteration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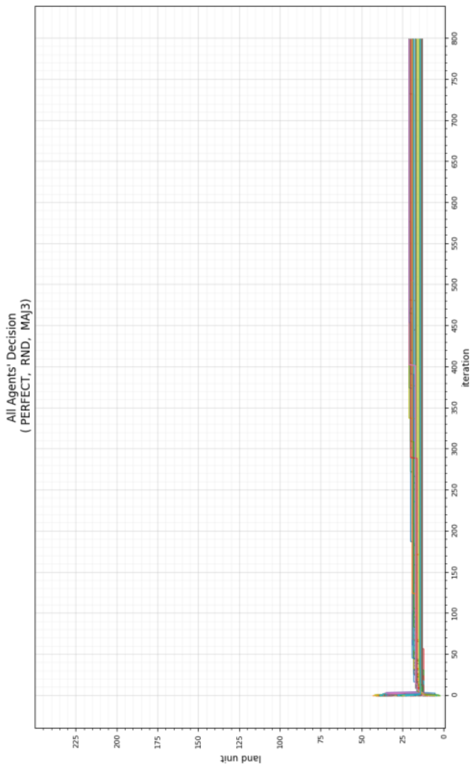
land unit
iteration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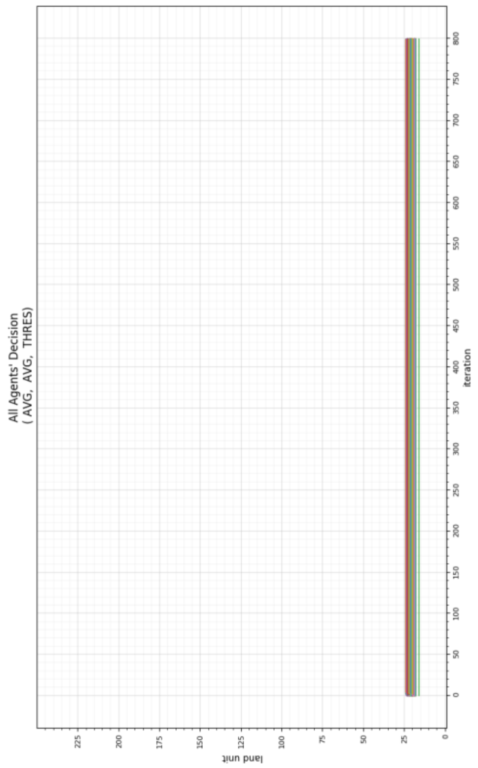
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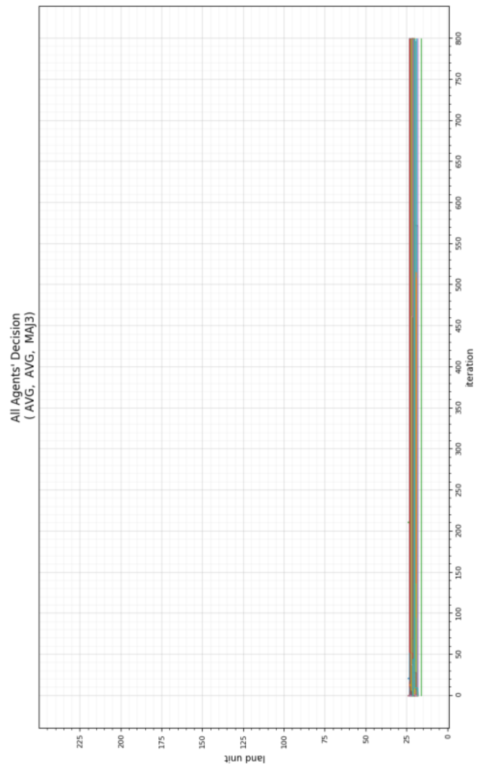
(AVG, AVG, THRES)
land unit
iteration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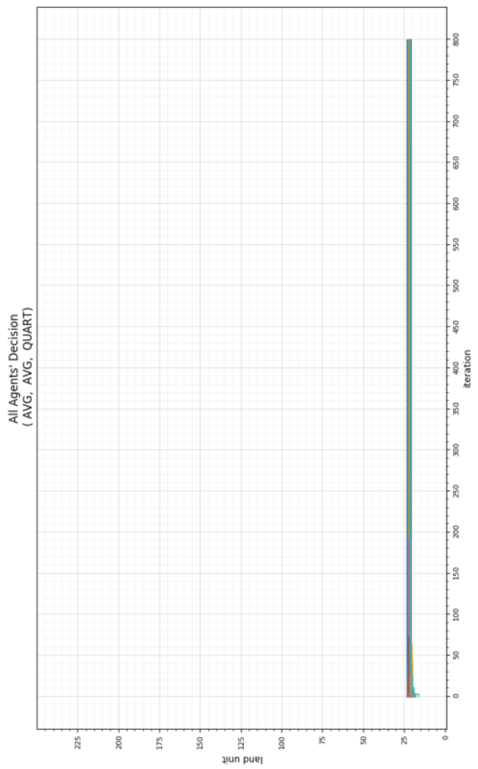
(AVG, AVG, MAJ3)
land unit
iteration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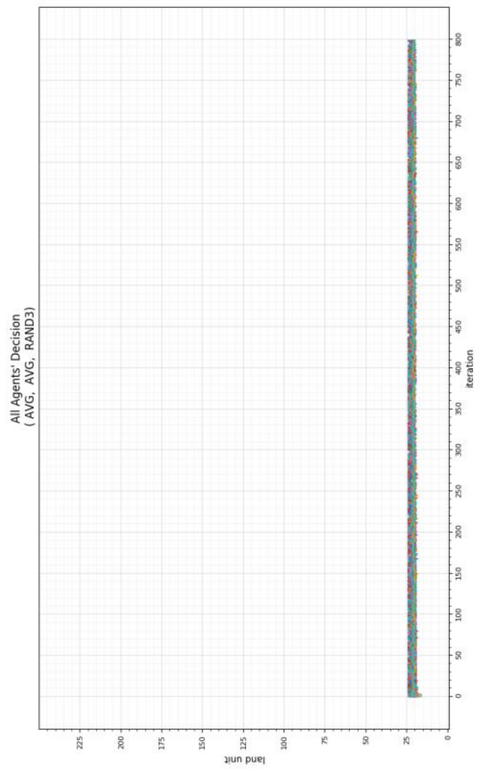
(AVG, AVG, QUART)
land unit
iteration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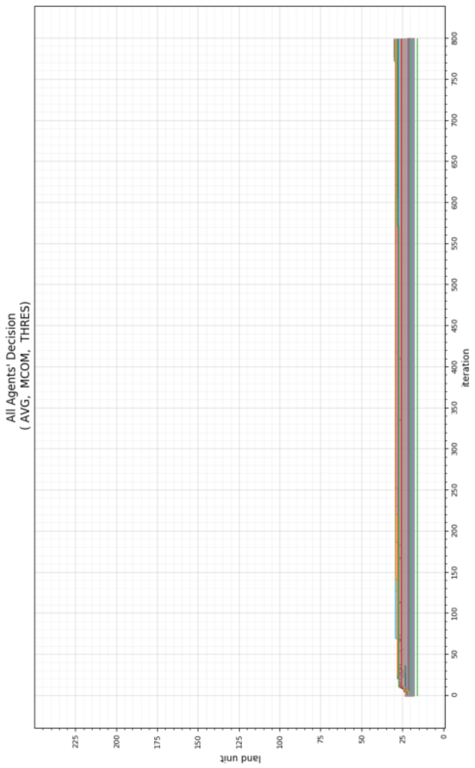
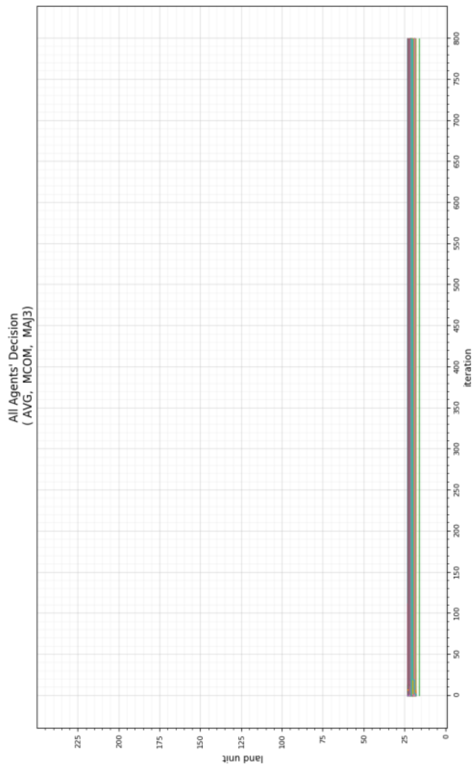
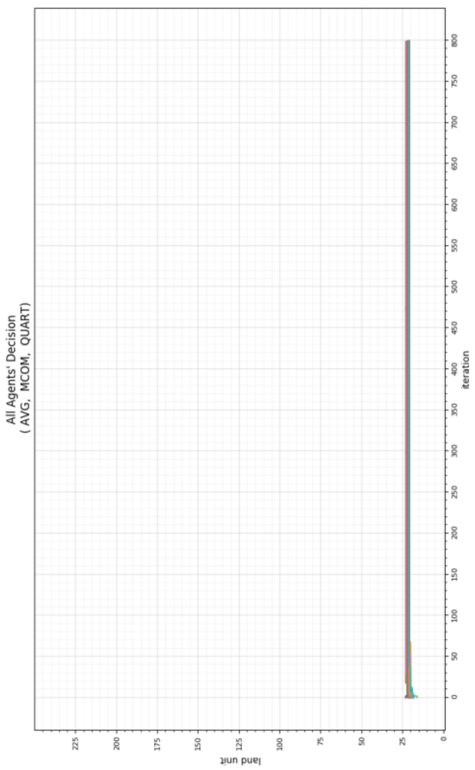
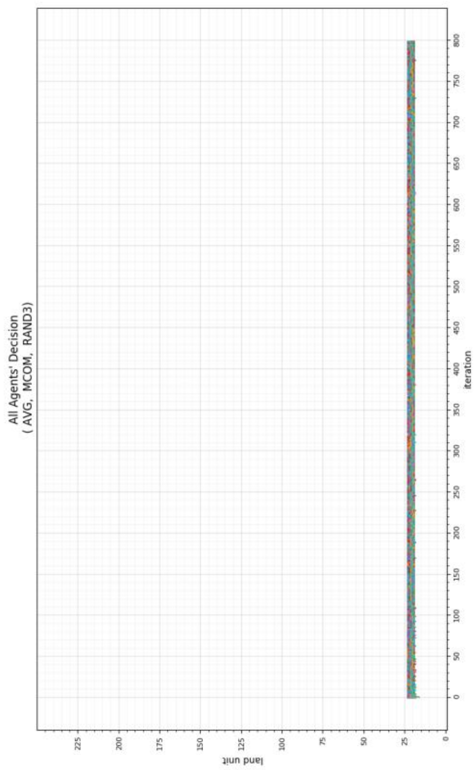
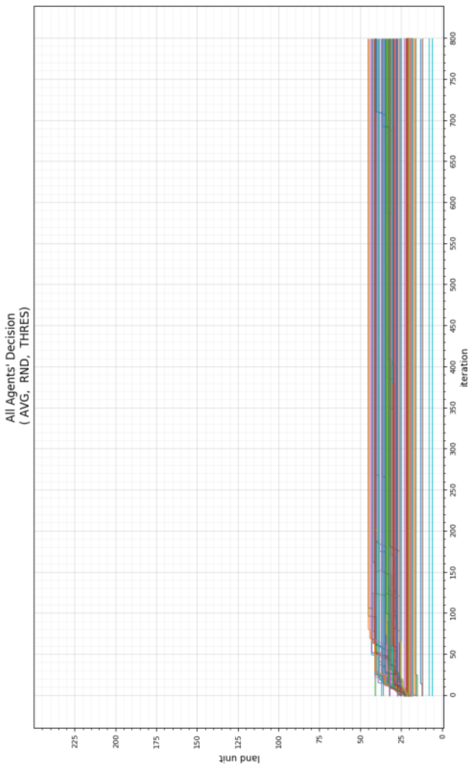
(AVG, AVG, RAND3)
land unit
iteration


All Agents' Decision
(AVG, MCOM, THRES)
iteration
land unit


All Agents' Decision
(AVG, MCOM, MAJ3)
iteration
land unit


All Agents' Decision
(AVG, MCOM, QUART)
iteration
land unit


All Agents' Decision
(AVG, MCOM, RAND3)
iteration
land unit


All Agents' Decision
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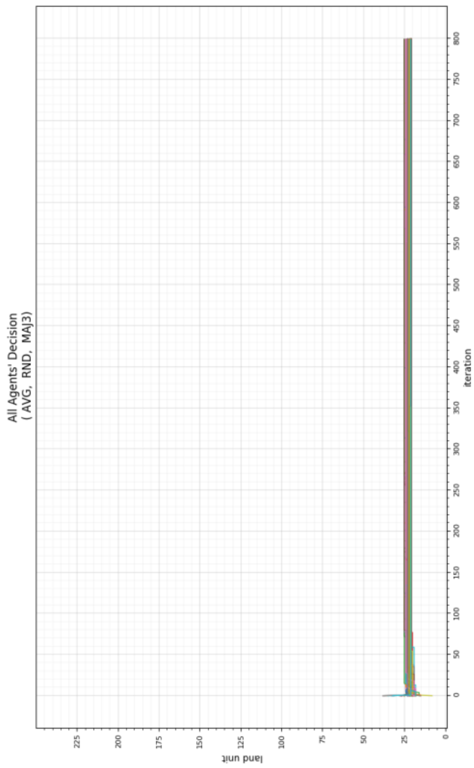
iteration
land unit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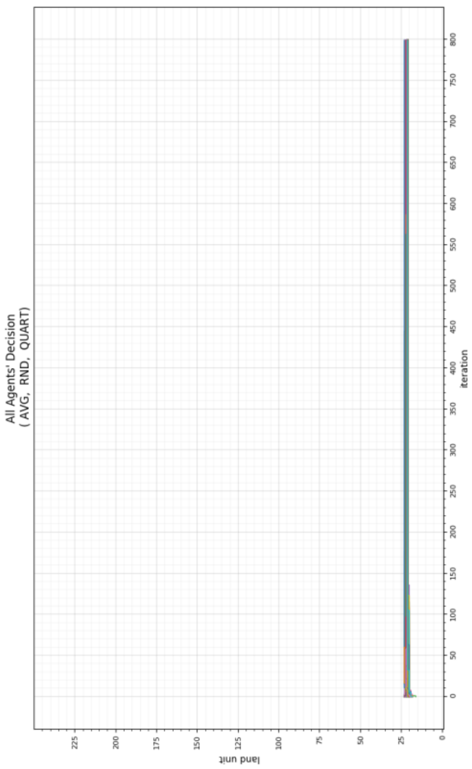
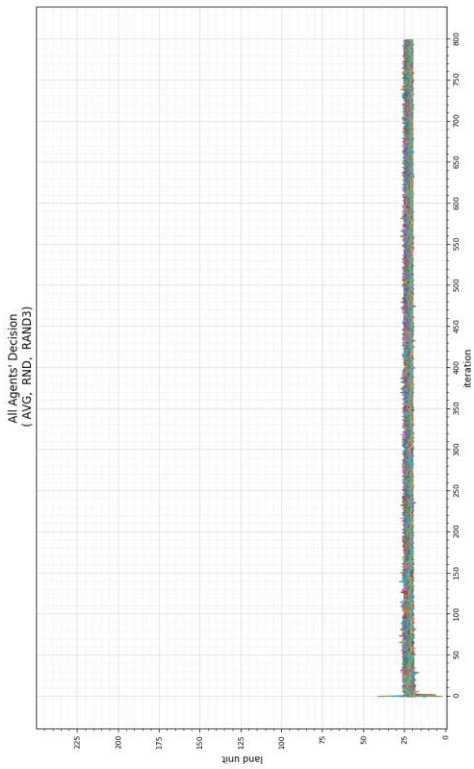
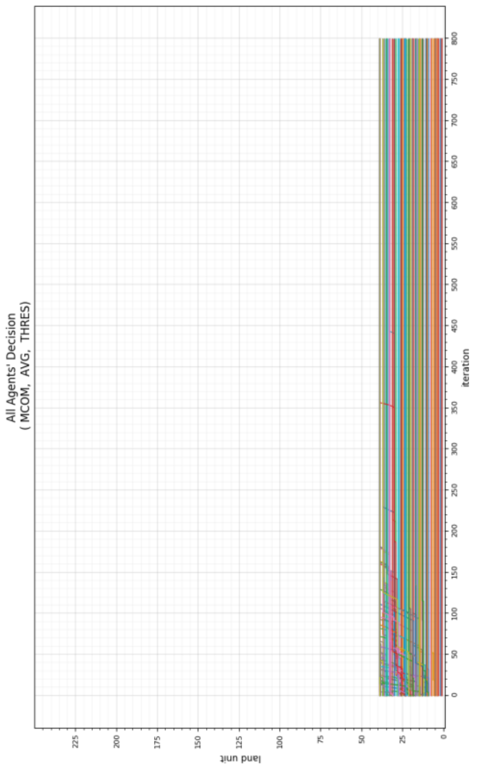
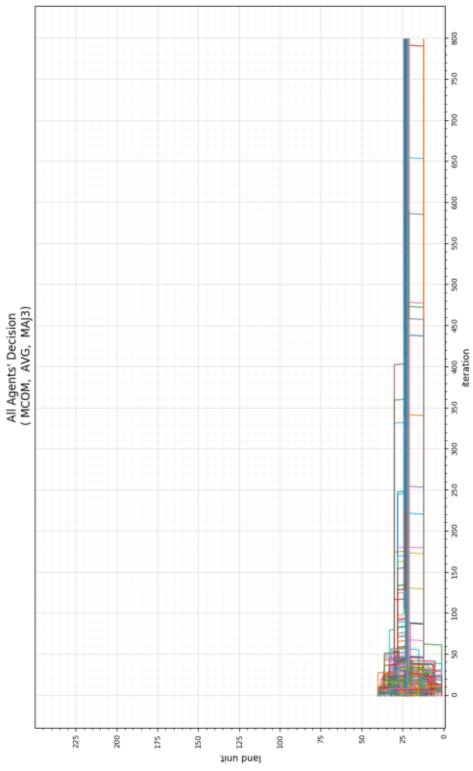
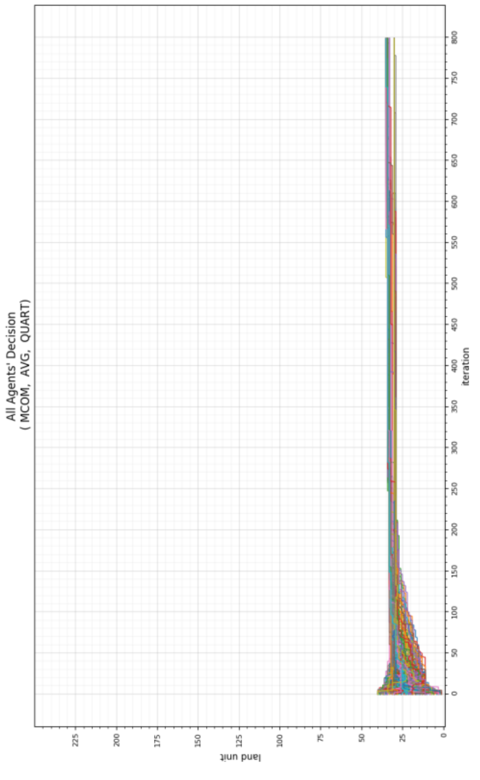
iteration
land unit

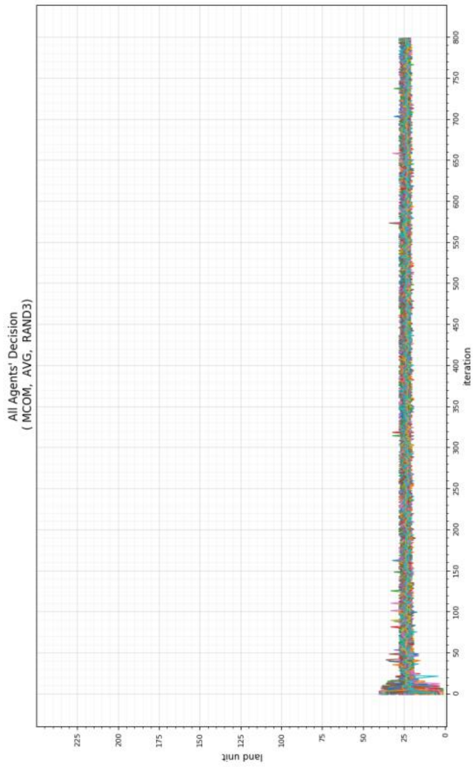

All Agents' Decision
(AVG, RND, QUART)
iteration
land unit


All Agents' Decision
(AVG, RND, RAND3)
iteration
land unit


All Agents' Decision
(MCOM, AVG, THRES)
iteration
land unit


All Agents' Decision
(MCOM, AVG, MAJ3)
iteration
land unit


All Agents' Decision
(MCOM, AVG, QUART)
iteration
land unit


All Agents' Decision
(MCOM, AVG, RAND3)
iteration
land unit