A Spatial Agent-Based Model of Social Relationality: Emergent Cooperation and Leadership in Community Development

By

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Abstract

The main objective of this research is to develop a spatially explicit agent-based model that simulates emergent cooperation and leadership in the context of complex community development. Formalization of the framework is founded on the postulate that cooperation and complexity leadership emerge from the non-linear behaviours of mobile affective agents as they participate in social interactions. The architecture is an object-oriented system of components that model mobility, social communication, psychological state, labour market dynamics, leadership, and evolutionary learning. As an approximation of real world decision-making, agents have an affective state derived from a psychological model that influences their participation and response to the outcomes of social interactions. The spatial context of these social interactions is based on the mobility dynamics of individuals as they probabilistically select an everyday activity in reference to their demographic states and expected payoff structure associated with potential neighbours. Social interactions are classified according to the type of neighbourhood required for its social network: (1) a grouping of multiple agents at a shared location, or (2) a directed pairing of employee-firm traders engaged in a labour market transaction. Social interactions in multiple agent neighbourhoods are simulated as N-Person's Prisoner's Dilemma games, where the action choices of the citizens are determined from the degree of relationality and trust within the social network. Labour market transactions are interactions between an employee and a firm who are paired with a preferential partnership matching mechanism. These directed social exchanges are modeled as two person's Iterative Prisoner's Dilemma games. Self-organizing leadership is conditioned on the tensions endemic in the Prisoner's Dilemma and the tensions purposely introduced during knowledge diffusion by the administrative leaders. The localized and overall cooperation and defection leaders are identified by the magnitude of their reward, and are tagged as the most successful individuals within the environment. The unsatisfied agents survive by adopting the action strategy of their highest paid neighbour implemented with a social mimicry mechanism. A form of steady state cooperation in a spatial environment depends on the citizens behaving

in a comparable altruistic manner by making affective decisions with similar action strategies.

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List of Abbreviations and Symbols

NPPD – N-Person's Prisoner's Dilemma

IPD – Iterative Prisoner's Dilemma

GIS – Geographic Information Systems

ABM - Agent-Based Model

ALMA - A Layered Model of Affect

OCEAN – Five Factor Model of Personality

PAD – Mehrabian Pleasure-Arousal-Dominance Mood Spacing

OCC – Ortony, Clore, and Collins Model of Emotions

FSM – Finite State Machine

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Part I: Introduction and Research Overview

1.0 Introduction

The practice of community development in rural Newfoundland and Labrador has undergone a number of philosophical and theoretical shifts since the province was incorporated into Canada in 1949. In the years after Confederation, the federal and provincial governments enacted programs and policies that promoted small scale manufacturing and large scale resource projects meant to industrialize the outport communities. As a top-down province wide approach, community development focused primarily on improving the economic conditions of the rural population, but failed to consider the social effects of these policies. This was especially evident with the household resettlement program that attempted to centralize the population to support the industrial growth. In the late 1970s and early 1980s, the provincial government established programs based on the notion that the underdevelopment in the outports could be solved by gaining control over the natural resources to increase employment in the communities. Although social and cultural issues were increasingly recognized, these approaches ignored the endogenous development by the people who live in these communities. In 1985, a Royal Commission on Employment and Unemployment was established to investigate the fundamental requirements for a program of social and economic development centered on the strengths and weaknesses of the local economy in the outports. The commission recommended that the best strategy for improving the economic and social conditions in the outports was a bottom-up approach of the citizens developing and implementing plans and policies that promote small-scale enterprise, entrepreneurship, and self-reliance.

House (1989) supported the findings of the commission with a proposed model of community development that would lead to a sustainable outport. He listed ten features that the model community should have for development to succeed, and then compared existing outports to the sustainable model to highlight issues that could hinder development plans. Two of the main constraints on long-term sustainability are the lack of entrepreneurship and the overreliance on unemployment insurance and short-term paid employment. Historically, entrepreneurship has been discouraged and suppressed by a local culture in the outports that frowns upon those individuals who are trying to “get ahead”. More importantly, entrepreneurs were often frustrated with the bureaucracy of rules and procedures that they experienced while applying for government funding and accessing development programs. There was also a pattern of short-term employment of people getting just enough weeks of work to qualify for unemployment insurance. The sustainability of the local economies was weakened by the labour market nonparticipation of those people who perceive long-term employment as undesirable. Any outport that strives to be a sustainable community will have to address these issues, but the community leaders may have a difficult time in convincing people to alter their behavorial patterns.

In the twenty three years since, government has made efforts to facilitate and support community development with the creation of a province-wide network of Rural Economic Development Boards (REDBs), a red tape reduction program, and departments, such as Innovation, Business, and Rural Developments, with a mandate to encourage and support endogenous growth. However, the success of a community development program will still be greatly dependent on the attitudes, beliefs, and decisions of the local leaders and entrepreneurs, specifically cooperatives and community organizations, as well as the average citizens who are not directly involved but may be impacted by the implemented plan. The basic social aspects of community development are the relationships and communications between the people, where individuals cooperate and exchange opinions and knowledge about potential courses of action to address the current and future issues facing the community. The participation of citizens in the decision-making processes enables the individuals who are entrusted with leadership roles to act on the community's behalf. From a social perspective, bottom-up development is a consensus building approach of citizens raising issues, listening to the views of others, and then cooperating to produce an agreed upon enhancement plan. These social interactions define the relationships that emerge between the participants and the sense of community that each person feels about belonging and mattering to the group.

A common question both in practice and in the literature is why community development works in one locality but fails in another even though both have similar social and economic profiles. The reason could be obvious with one community being closer to a natural resource, having access to a major highway, or falling within the urban shadow of a large metropolitan center. However, an alternative explanation is that the difference in community development success is attributable to the citizens themselves, with one community possessing a more motivated and knowledgeable development team that its counterpart. In this thesis, bottom-up community development has a different connotation than the standard interpretation as the consensus plans of the community. It is hypothesized that a model of community development can be formalized as a social relationality network defined by the actions and decisions of people in the community. This requires a systems approach of community development implemented as an individual-based model, where the macro-level structure and conditions of the community emerge from the behaviours of the individual citizens. The dynamics of the participation and behaviours of each person as the community first works towards and then implements a consensus course of action is the focus of this thesis, rather than the development plan itself. For example, leadership is known as an essential element in empowering and mobilizing the population to get involved in community development. Leaders can be people who are appointed to positions of authority by their neighbours, but they can also emerge during social interactions due to their personal traits (e.g. charismatic personality) or dedication to the development program. At the micro-level of individuals, community involvement is the conscious decisions of people to exchange information and opinions amongst themselves while participating in the development processes.

The motivation for the research on the dynamics of community development using an individual-based model stems from several pragmatic considerations. Firstly, individual-based models can simulate phenomenon, such as the emotional conditions of the citizens, which are impossible to model with deterministic equation-based approaches. Secondly, an individual-based model can investigate the dynamics of a community from the perspective of an individual person. Each person in a community can be represented and modeled as an affectively enabled individual who interacts with others citizens during the processes of community development.

An affective individual will experience emotional and mood state changes as a consequence of social exchanges, which contributes to his self-identity in the community. A person will believe that he belongs to a community when his opinions are valued and his participation in the social interactions leads to a positive affective state. This sense of belonging to the community will encourage the individual to cooperate during the decision-making process, and the more people who cooperate, the stronger the social capital of the community. A primary effect of person-to-person communication in community development is the diffusion of information, but it also provides a secondary function of evaluating the social positioning of individuals in the community. As a person reaches and sustains a high social standing, he can emerge as a community leader to a point where average citizens trust him to decide the direction and focus of the development plan. The benefit of an individual-based modeling approach is that the success or failure of the development plan can be related to the strengths and weakness of the leader in his dealings with government, motivation of the citizens, and understanding and acceptance of what can be realistically improved in the region.

The third motivation for this research has to do with the history of change in the provincial government in designing and implementing policies related to community development. The current direction of rural development in this province is towards a regional long-term sustainable development rather than endogenous, municipality-specific development. As an individual-based system, the implementation of this model will remain the same regardless of the geographic scale of the social confluence area. Whether a neighbourhood, municipality, region, or the entire province, the processes of community development depend on the decisions and behaviours of the people within the modeling environment.

Individual-based models of social phenomenon are normally developed as computational models of complex adaptive systems. This research follows the common choice of developing and implemented a complex adaptive system as an agent-based model, except that it is spatially explicit since the individuals have the ability to move throughout the modeled area. Each agent is a computational object that represents a simplified version of an individual entity in the environment, agents represent anything from a human being to a firm to a physical infrastructure feature, such as a road or building. The interactions between agents are modeled with simple sets of rules, but lead to complex behaviors that self-organize the modeled community.

The ground of many studies of community in human geography is the ensemble of activities and relationships among people across space and place. A community can be conceptualized as a structured environment of social relationality that is constantly reconfigured as people pursue the activities of everyday life. This concept of community can then be implemented as a generic modeling environment that simulates all of the communication and personal exchanges within the different types of social networks: pairs of people, small localized groups, or the entire community. The design of a social relationality model must be able to handle the different types of social networks but also the different types of social interactions.

The various types of social interactions are generally associated with the everyday activities undertaken by the people in a community. There are short-term incidental meetings between people and the longer term habitual events of daily life. An example of an incidental meeting would be small talk amongst a group of consumers in a supermarket. Habitual activities, such as a school day or employment shift, are interaction episodes where the same group of people is relationally connected for an extended period of time.

Markovsky and Willer (1988) state that the different types of social interactions can be viewed as power relationships. In a power relationship, a degree of control and persuasion is either implicitly or directly associated with particular individuals in a social network. These authoritative people have the ability to influence the decisions and behaviours of the others in the social group. The locus of a power relationship depends on the intensity of the control exhibited by these socially dominant individuals. The submissive individuals relinquish their degree of control, because of the financial, emotional, or social benefit of membership in this grouping.

The incidental meeting and habitual events are usually at the opposite ends of the spectrum of power relationships. The individuals maintain their control in an incidental meeting, because they have little to gain or lose from these short-term social exchanges. As humans are cognitively selfish, certain individuals will attempt to and may dominate the interaction, but their opinions and advice will have minimal effect on the decisions and behaviours of the others.

For the habitual interactions, the power relationship is often socially one sided with one individual leading the decision choices of the social network. Teachers dictate the course of an educational session with minimal interference from the students, because the students understand the knowledge benefit of paying attention in class. Workers accept the authoritative position of the managers at an employment facility, because the financial survival of the workers may be dependent on obtaining and maintaining a work contract at these firms. The higher intensities of control of social interactions in the settings of habitual daily activities arise and are maintained, because the familiarity that an individual has with dealing with the same people will enable him to trust one of them as a social leader. Between these two extremes are the power relationships with varied control structures where the decisions of the people are influenced by memories of past interactions and the anticipated outcome of the current social exchange.

Each individual in a power relationship will experience the interaction in a different way based on his personality and emotional appraisal of his position in the social network. This affective state shapes an individual's sense of community in terms of a personal feeling of belonging, emotional connection to others, and the perception of having a degree of influence in the social network. An extroverted person with a charismatic personality may be able to convince others to allow him to assume control in the power relationship. People who are continually happy with the outcomes of social interactions will feel that they belong to the community, because they believe that they can anticipate and trust the behaviours of their counterparts.

The spatial connotation of a "community of place" is a shared physical interaction network and regular communication among residents about common issues and interests. Place in this sense is defined as a social region delineated by the movement of people as they travel to distinct locations to engage in activity-specific interactions. The destinations for these movement episodes, often buildings, provide a meaningful point of reference for the social interactions. Also, individuals will move multiple times throughout the environment as they engage in a series of activities that typify a day in the life of an average person. From a modeling perspective, each movement event will reconfigure the immediate social structure and spatial extent of the community.

The design of a realistic model of a community requires a bottom-up approach of modeling the processes of social relationality according to the behaviours of affectively enabled individuals that generate the complex macro-level system structure. Human interactions are face-to-face social exchanges that occur at the micro-level of individual people. At this scale, the behaviors of the individuals can be unpredictable and stochastic so a top-down modeling approach based on a set of generalized behavioral equations or rules would be problematic. This micro-scale unpredictability reflects the fact that a community of socially interacting people is a complex system, with complex referring to the many non-linear relationships between people and to the fact that these relationships are the result of processes that are spatially and temporally dynamic. Each person can vary in his memories, experiences, knowledge, and desires so it is not useful to analyze a social community as the macro-scale, because the behaviours of the community will emerge from the actions choices and decisions of the constituent individuals. For these reasons, the intention of this research is to develop a formalization founded on complexity theory that will model a community as a complex adaptive system of social relationality.

In the domain of geographic complexity, the relationality between constituent elements of a human system sets the focus on how the spatial variability and social interactions between people and the environment produce emergent system behaviour that in turn acts back on the individuals, altering and guiding their behaviours and decision-making. Several authors (O'Sullivan 2004; Manson, 2007) present this form of aggregate complexity as a relational view of space, which involves the study of local attributes of physical locations, interactions among individuals at neighbouring locations, and information flows along these interaction networks. Thus, community as a complex adaptive system must represent the individuals, define the relationality among them according to a set of theoretically supported assumptions, and capture the role of the spaces in which they exist and are related.

Hazy (2007) reviewed numerous distinct approaches synthesized as complex adaptive systems in computer models of social behaviours, and determined that agent-based modeling is a preferred method for simulating the processes in a human system. Agent-based models are generative bottom-up systems that consist of a set of agents that simulate the behaviours of the various individuals that make up the system. A spatially explicit agent-based model of a human system is based on two universal concepts essential for generating adaptive social networks: the processes that bring about the relations, and the internal structure of the network (Alam and Geller, 2012). Process and structure are linked when the agents are placed within the system according to their social and geographic positioning. The concept of a community is premised as a well-connected relational structure of networks defined by a set of processes and reconfigured by the phenomena that emerge from social interactions.

Gilbert (2004) suggests that the design of an agent-based model should consider existing theory to articulate its purpose, and its baseline architecture should concentrate on the central processes of a number of important aspects in the theoretical application. Onyx and Leonard (2010) present a complexity perspective of a well-connected community as a geographic confluence of social engagement across multiple overlapping networks of people in activities geared towards community development. In practice, community development from a complex systems perspective is a specialized goal-oriented form of social relationality, but its abstract framework is based on processes and emergent behaviours common in studies of social networks, specifically social interactions, cooperation, trust, and leadership. The postulates of community development from a complexity perspective provide the epistemological direction for developing and utilizing the model in this research.

The aim of this research is to develop a spatially explicit agent-based model to simulate the nonlinear dynamics of social relationality in a generic rural community that is characteristic of an outport in Newfoundland and Labrador. As a sociological subject and geographic object, the emergent community depends on the mobility behaviours and social decisions of individuals across a range of micro-level relationships of different types and strengths. It is also imperative that the influence of administrative norms and macro-level emergent phenomena on the decisions and behaviours of the agents be considered, because individuals can reason and act on the macro-level features of the social networks that they are part of (Gilbert, 2004). An undervalued aspect of human decisions in social agent-based modeling is the affective state of the individuals in the anticipation and response to the personal gains or losses from memberships in these interaction relationships. Kennedy (2012) argues that the design of an agent-based model of a human system needs to be cognitively enhanced to consider how the emotional states of individuals influence their decisions in social exchanges. Therefore, a better approximation of realistic human decision-making has to consider how an individual's emotions, mood, and personality generate stronger or weaker relational ties in the networks, and how the affective states of the citizens influence the level of social identity in the community. Formally, the architecture of the model must be an integrated system of methods that simulate the different types of relationships that individuals could participate in, and a mobility mechanism to simulate the variability in the spatial positioning of the agents as they move throughout the environment to engage in everyday activities. Heeding Gilbert (2004) about limiting the scope of an agent-based model to avoid over-complication of its architecture, the everyday activities that the individuals can pursue are limited to social interactions specific to definable processes of community development. Social relationality in the context of community development will depend on the emergence of cooperation and leadership in the localized social interaction networks.

Studies in the social and computer sciences have utilized the Prisoner's Dilemma (PD) to analyze the emergence of cooperation in social environments (Trivers, 1971; Axelrod, 1984; Brembs, 1996). The Prisoner's Dilemma is a social coordination game that simulates the emergence of cooperation among the same set of non-discriminatory agents who interact and learn synchronously. In this model, the formalization of the Prisoner's Dilemma game is conditioned on the number of individuals in the social grouping and the relationality structure of certain everyday activities. The Iterative Prisoner's Dilemma (Axelrod, 1984; Boyd and Lorderbaum, 1987; Nowak and Sigmund, 1992) is a non-zero sum game played between two individuals who can choose to either cooperate with or defect from the other player. There are two situations where the social interactions are modeled as communication events between a pair of individuals: (1) the social group only consists of two people, and (2) for a social group of more than two people, the everyday activities are implemented as two person power relationships between each possible pairing of individuals. For example, there may be ten patients in the waiting room of a medical clinic, but a physician will communicate with each person individually in a separate social exchange.

For all other neutral power relationships (all individuals have some level of control) with more than two people interacting, the N-Person Prisoner's Dilemma simulates the collective actions and behaviors in social groups. During an interaction episode, individual players may cooperate with each other for the collective good of their social environment, or they may prefer to pursue their selfish interests. The incentives to cooperate may depend on how many players are contributing to the group and the effect of their actions. In multi-player interactions, cooperation and social cohesion emerge from the consensus behaviors and actions of the social unit. In this research, the N-Person Prisoner's Dilemma is used as a generic approach of social interactions in a spatial neighbourhood, and does not represent a specific type of relational situation between the individuals.

The localization of social groupings is directly associated with the mobility events of individuals to locations of specific activities. For example, an agent travels to the nearest supermarket to purchase groceries and encounters other consumers at the same location. Once the temporary social groups are formed, the goal of the N-Person Prisoner's Dilemma game is to only simulate the processes of social interactions and determine whether a series of outcomes make the individuals more cooperative and trusting, and does not represent the processes of simulating the particular everyday activity itself. Simulations runs investigate the spatial dynamics of the emergence of cooperation and leadership in a community of social interaction networks, where altruistic behaviours of the agents are essential to strengthening the degree of communal relationality and social identity.

1.1 Agent-Based Models

Originated in the field of Distributed Artificial Intelligence, agent-based models are based on the principles of distribution and interaction (Ferber, 1999; Weiss, 1999). Agent-based models are comprised of a community of agents. An agent is an autonomous entity that is able to act locally in response to stimuli from the environment, to communicate with other agents, and to have goals that it aims to satisfy. Ferber (1999) defines an agent as:

> *"a real or abstract entity that is able to act on itself and its environment; which has a partial representation of its environment; which can communicate with other agents; and whose behavior is the result of its observation, knowledge, reasoning, and interactions with the other agent"*

The goal of agent-based models of human systems is to enrich the understanding of the macroscale phenomena that may emerge in the system. The characteristics that are supported by the agent in a model will ultimately depend on the context of the project. However, there are seven general characteristics that commonly form the core characteristics of an agent (Wooldridge and Jennings, 1995; Benenson and Torrens, 2004).

First, agents are autonomous and heterogeneous, which means that they act based on their own experiences. An autonomous agent operates without the direct intervention of others and has control over its actions and internal states.

Second, agents are proactive and reactive. An agent is proactive when it exhibits goal-directed behavior to control its own behaviour in spite of changes in the environment. Reactivity is the ability of an agent to sense and act as a result of changes in the environment (Cristo, 2001). In this case, an agent perceives an environment, and a change in that environment affects its behavior.

Third, agents have the ability to perceive their neighbours and be aware of the opportunities and problems they offer.

Fourth, agents can exhibit sociability, which allows them to communicate with other agents and entities. Communication is one of the most important characteristics necessary for agent interactions and is the basis for the emergence of collective behaviors.

The fifth characteristic of an agent is that it is adaptive, and it can learn and improve with experience. An agent uses its experience and knowledge to learn, and to change its behaviors based on this learning.

Sixth, an agent has an identity that contributes to its sense of individuality and recognition. Identity refers to the associated attributes assigned to an agent, such as gender, marital status, age, etc. When interaction starts, the identity attributes of the agents enable them to know whom they are dealing with and how they should approach them in a communicative manner.

Finally, an agent can be mobile and can travel about the system according to its sense of space. Agents can be static, but they can also be non-fixed entities that know where to go, when to go, and how to go there. During this movement, the sense of place orients the agent to be aware of its own location as well as where other destinations, objects, and agents are situated.

Agent-based models are designed to simulate the behavior of these agents as they interact with each other and with their environment using simple local rules. The application of these rules will differ depending on the local characteristics of each agent. Thus, the rules are handled autonomously and independently at the level of each agent, but their functioning takes into account the characteristics of the surroundings through the interactions between different entities.

1.2 Social Relationality in a Community Context

Lichtenstein *et al*. (2006) describe social relationality as an emergent phenomenon from the non-linear interactions that occur between the "spaces between" individuals within a social network. In this context, space is a sociological subject concerned with the bonding or sense of closeness that emerges from the communications and knowledge exchanges between individuals. Relationality is thus an adaptive process based on the shared understanding of the associations that constitute particular social connections. Individuals develop a sense of bonding, often varying temporally, when their interests and opinions are closely aligned with those of the interaction grouping. Thus, a social network consists of evolving connections and interdependencies between people rather than the selfish actions of individuals.

The social aspects of the "space between" individuals are shared with the relational view of the space of aggregate complexity, but the geographic variability of where the individuals are situated when they engage in a social interaction differentiates the approaches. However, several researchers (Gilchrist, 2000; Onyx and Leonard, 2010) present relationality as an emergent dynamic within a "well-connected" community, an interaction space that is both a sociological subject and geographic object. A relational community is conceptualized here as a geographic confluence of social engagement across multiple overlapping networks of interacting and interdependent agents. The self-organization of the internal structure of a community will depend on the positioning of the agents in the social interaction networks as each individual goes about their daily life. Yamakawa *et al.* (2005) define social positioning as a dynamic form of social role determination contingent on the learning and recognition of the importance of individual social relationships in a community. As such, social positioning is the level of trust associated with an individual as a consequence of the altruistic and beneficial (socially, financially, emotionally, etc.) behaviors in past interaction episodes. Individuals in high social positions often emerge as leaders within the community and are actively sought out by others wanting to exchange information, opinions, and knowledge with them.

Bradbury and Lichtenstein (2000) explain that social positioning in relationality depends on the vividness and locus of the interactions within the social networks.

Hess *et al.* (2009) demonstrate that vividness of interactions depends on the social presence of individuals, with the intensity of vividness strongest in face-to-face communication. As such, vividness refers to the degree that interpersonal relationships are visible and quantifiable according to the similarity of each individual's self-identity and their perceived social identity of the collective. The strength and temporal constancy of the connections that an individual associates with others will depend on the emergent level of cooperation in the decisions of the social grouping. Also, cooperation is an integral mechanism in a tendency toward homophily in a social network, where the greater the similarity between the individuals the more likely it is that they will establish and maintain a social connection (McPherson *et al*., 2001). Homophily is the tendency of individuals to associate and bond with others who share common characteristics, such as social position or type of occupation (Cohen *et al.*, 1998). An individual’s sense of self in the community is an indication of the social and emotional profitability of membership in a social network, which has been measured as individual utility levels in several agent-based models of relationality (Tesfatsion, 2001). The vividness of the interaction can be determined with a simple comparison of the utility level of each individual and the average utility values for all citizens in the community.

The locus of interactions refers to the different types of relations that can occur within a community: dyadic pairings, small aggregate clusters, the entire population, etc. The temporal and social elements of the locus of interactions are conditioned on who initiates the contact in a relationship and whether an individual(s) has a level of authority or influence in the communication exchanges. Individuals of lower social position may intentionally initiate a relationship with a leader to learn what traits and behaviors they could imitate to improve their social standing. Authority and influence are characters of power relationships (Mann, 1986, Markovsky and Willer, 1988), where a level of control is either implicitly or directly linked to certain participants in a social exchange. The socially forward person in a power relationship has the ability to influence the behaviours and decisions of his subordinate neighbours for either personal advantage or for the self-perceived benefit of the collective.

An example is an employee-firm interaction network in an asymmetrical labour market. Depending on the market conditions, such as the wage rate, unemployment rate, and job vacancies, the locus of control falls to the participant who has the less to lose if the results of an interaction episode are mutually self-rewarding. Take the case where there are a large number of potential employees interacting with a firm tasked with filling a single job opening. The likelihood is high that many of the employees will purposely exhibit altruistic behaviours and set the locus of control to the firm in an effort to differentiate themselves from the other candidates. The firm has exclusive control over who is selected as the job partner, and the choice could be the individual that the employer believes can be exploited to obtain some level of payoff.

An often overlooked factor in the locus of interactions is the affective states of the participants in these social interactions. An introverted personality could be a contributing cause as to whether a person intentionally avoids social contact, while a charismatic extrovert could emerge as a natural leader in the environment. The emotional aspects of the personal connections, feelings such as joy, distress, admiration, and reproach, exert an influence on how individuals both anticipate and respond to the consequences of each interaction event. For example, an individual who becomes angry has entered a mood state where his level of social dominance rises, and can increase to a point where he forcefully takes control of the social interaction (Mehrabian, 1996).

Spatial positioning in the well-connected community refers both to the spatial variability of where the entities are situated and the mobility dynamics of the human population. At an abstract level, a typical community consists of both fixed and mobile geographic entities. Fixed entities are the non-mobile objects that comprise the infrastructure footprint of a community: buildings, roads, parks, water features, etc. A relational view of fixed space is primarily concerned with the spatial proximity of the infrastructure objects and how their characteristic attributes influence the formation of social networks. Changes in the physical state of a fixed object could impinge and alter the states of its fixed neighbours. For example, the levee of a river could break and the flood water spill onto a road network making it impassable. Yet, the infrastructure pieces in a community mostly function as the origins and destinations for the mobility behaviours of the social entities. Networks of social interaction are constructed and reinforced as people move throughout the system as they pursue the activities of everyday life. Whether due to the anticipation of a positive experience in the social exchange or the residency of a person of high social position, individuals will purposely travel to the locations of specific infrastructure facilities that house these activities. The locus of interaction can play a role in the place-dependent trajectory of social bonding in the localized subpopulations of people who emerge within the system. A complex adaptive system model of a well-connected community can be developed as a spatial agent-based model that simulates relationality as the product of the adaptive dynamics of both the geographic topology and social connectivity networks in the simulated environments.

2.0 Statement of the Objectives

The main objective of this research is to develop a spatially explicit agent-based model of a relational community and to simulate the principal processes associated with human positioning in socio-geographic interaction networks. The framework will simulate the dynamics of a community with the decisions and behaviours of affectively enabled human agents, with the social bonding depending on the emergent cooperation within the environment. Agents who attain a level of trust can assume the role of a leader and direct the course of action of the plans and policies to better the social and economic conditions of the community. Gilbert (2004) comments on the strategies of building socially oriented agent-based models, and suggests that the art of modeling is to keep the baseline framework as simple as possible. The research scope of human positioning is immense, involving aspects of sociology, psychology, geography, economics, and many other disciplines. A model of relationality comprising all of the functions, processes, and methods of each research discipline would be theoretically impractical and computationally very expensive. Also, the design of a model should be based on existing theory to aid in deciding what factors are important to clearly articulate its purpose and to ensure its capability of generating useful information (Gilbert, 2004). With a well-connected community as the simulation environment, the theoretical basis for this model comes from the field of community development.

It is important to note that the model in this thesis only integrates the characteristic processes universally associated with community development to formalize a methodology of simulating social relationality in a generic community. To comprehensively model the dynamics of community development, major components that simulate culture, economy, and the natural environment would have to be included, and that is beyond the scope of this thesis. Also, processes directly tied to social relationality, such as volunteerism and empowerment, would have to be modeled. In its current form, the framework for this model encompasses only a subset of the complete range of processes involved in community development.

2.1 Community Development as a Complex Process

Onyx and Leonard (2010) describe community development as a complex system of nonlinear processes that emerge from the actions and initiatives of people as they utilize the embedded social capital within a community. Similar to Shaffer *et al*. (2006), community development is pictured as a star-like embodiment of interacting spatial, economic, psychological, and social processes (Figure 2.1). At the top of the star, the human resources are the agent population: each individual is assigned a personality as well as state variables that determine his social position and spatial location in the network. The decisions and behaviors of each agent will alter his affective status and states in function of a set of transition rules and in conjunction with institutional conditions and the global consequences of his interactions. Rules and institutions guide the behaviors and decision making of the human agent. Institutions are governance networks that set the rules for using a community's social and labour market capabilities. Rules provide the agent with a form of intellectual ability to interact and communicate within the environment. Intelligence relates to an agent's cognitive ability obtained from its set of transition rules that handle its state, location, and neighbourhood interactions.

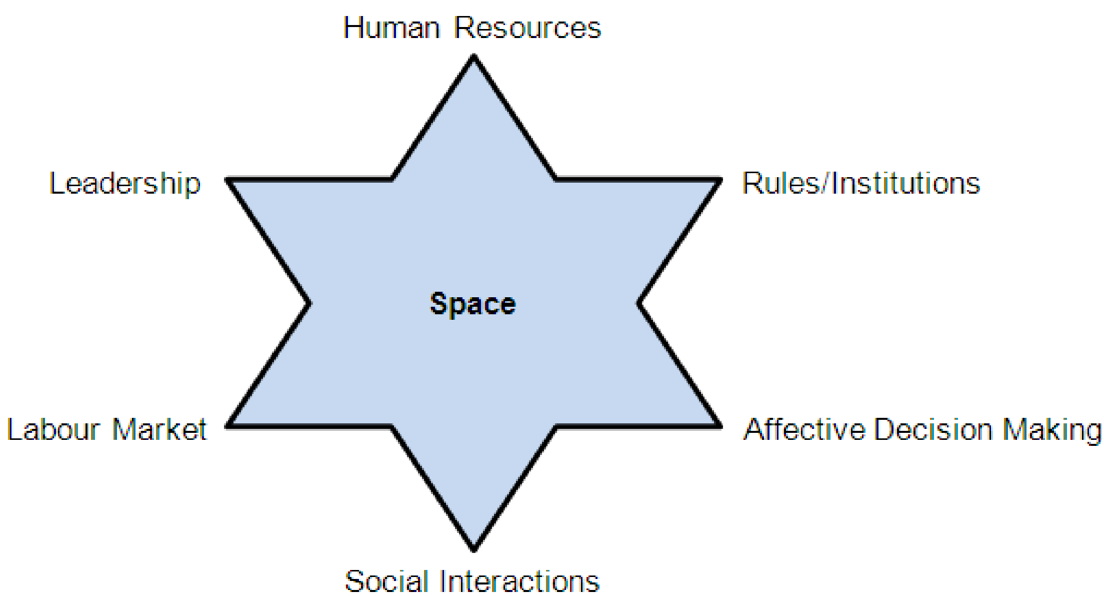

Figure 2.1: The Processes of Community Development

Decision-making is the primary evaluation process in a human system, where people communicate to identify values and issues in the community. These social exchanges allow people to participate and cooperate in collective problem solving. A standard for the agent-based modeling of power relationships is the Prisoner's

Dilemma. Yet, an underdeveloped aspect of the Prisoner's Dilemma is the affective state of the agents as they engage in the social interactions. The locus of interactions requires the emotional and mood states of individuals to determine their reactions to the outcomes of these communication events. In addition, decision-making in the different types of power relationships requires the social interactions be implemented both as multi-agent and dyadic exchanges, the later specific to labour market interactions.

Social interactions are tied to decision-making when agents have actively chosen to pursue an activity in the community that brings them in close proximity to other agents. Social interactions are the knowledge exchanges that occur amongst the individuals, and the results of these exchanges will determine the cooperation and leadership structure in the community.

Labour market exchanges are directed social interactions that are intended to establish an economic relationship between an employee and a firm. Agent-based labour market interactions have been simulated as Trade Network Games (Tesfatsion, 1997; 1998; 2001; Kitcher, 1998; McFadzean and Tesfatsion, 1999; Pingle and Tesfatsion, 2001, Hauk, 2001), and this approach can be modified to consider geographic distance in the evaluation of expected payoffs for relational matching. A spatial labour market game component simulates a two-sided market of employees and firms with choice and refusal behaviors and the option of non-employment. Cooperation emerges from the relationality and trust between pairings of trader agents as they participate in a labour market power interaction.

Leadership structure involves the complex interplay between administrative coordination and adaptive enabling in the social interactions. Modeling of emergent leadership depends on the tensions in the social interactions and the dissemination of information and opinions throughout the environment by socially influential individuals (Lichtenstein *et al.*, 2006). The altruistic state of a social environment depends on the survival and reputation of the overall cooperation leader(s) and the social mimicry of successful action strategies by the unsatisfied agents (Zimmermann and Equíluz, 2005).

Space is the central coordinating element that integrates all of the aforementioned processes, because all instances and manners of social interactions happen somewhere within the geographic confluence of the community.

2.2 Framework of an Integrated Spatial Agent-Based Model of Relationality

The computational architecture is the object oriented implementation in Repast of a heuristic approach to modeling the nonlinear dynamics of spatial mobility, social communication, psychological state, labour market dynamics, emergent leadership, and evolutionary learning. The heuristic sets are comprised of both bottom-up and top-down interaction rules that simulate the behaviors of the agents, who are represented as autonomous objects of knowledge and action.

The first step in achieving this objective is to devise a methodology for simulating the behaviours of mobile agents in a community. As an approximation of real world decision-making, agents have an affective state derived from a layered model of affect (personality, mood, and emotions) module that influences their participation in and response to the outcomes of social interactions. The spatial context of these social interactions is based on the mobility dynamics of individuals as they probabilistically select an activity in reference to their demographic states and the expected payoff associated with potential neighbours. The possible activities are geographically classified according to the type of neighbourhood required for the corresponding social network: (1) a grouping of multiple agents at a shared location, or (2) a directed dyadic pairing of employee-firm traders engaged in a labour market transaction. Social interactions in multiple agent neighbourhoods are simulated as N-Person's Prisoner's Dilemma games, where the action choices of individuals are determined from the degree of relationality and trust within the social network. Labour market transactions are preferential partnerships between an employee and a firm who are matched according to expected payoffs. These directed social exchanges are modeled as two person's Iterative Prisoner's Dilemma games. Emergent leadership is conditioned on the tensions endemic in the Prisoner's Dilemma and the tensions purposely introduced during knowledge diffusion by the administrative leaders. The localized and overall cooperation and defection leaders are identified by the magnitude of their rewards, and are identified as financially successful within the environment. The unsatisfied agents survive by adopting the action strategy of their highest paid neighbour in a form of evolutionary learning implemented with a social mimicry mechanism. The underlying principle of this model is a form of steady state cooperation in a spatial environment that depends on the citizens behaving in a comparably altruistic manner by making affective decisions with similar action strategies.

The next step is the simulation runs of “what if” scenarios that investigate the dynamics of the processes of each model component independently and then as a comprehensive system. The findings from each set of simulations illustrate how cooperation and trust depend on the familiarity between the agents and the size of the interaction neighbourhoods. Also, the simulation results for each model component were important for the testing of the functionality of the subsequent model additions. For example, context preservation was fundamental to the emergence of cooperation in N-Person Prisoner's Dilemma module, and cooperation leads to positive emotional and mood states in the layered model of affect. Thus, interactions with the same set of affective neighbours lead to positive appraisals of the actions of the agents and improved the likelihood of further cooperation in these social networks. Simulations of the integrated model investigated the different types of social relationships that comprise the daily activities that occur within a community. Scenarios with varied labour market parameters and activity specific interaction periods demonstrated that the type of relationship and the locus of control in the interaction neighbourhoods led to the self-organization of the cooperation and leadership structure in the simulation environments.

3.0 Model Testing and Assessment

One of the fundamental aspects of this research is gauging the utility of the model through calibration, verification, validation, and sensitivity analysis. Calibration improves the agreement between model outputs and a real world dataset by adjusting initialization parameters. Verification is the testing method that evaluates the degree to which the computational and mathematical components of the model generate expected behaviours relative to the theories that the model was developed with. Rykiel (1996) describes validation as the procedure of demonstrating that a model possesses a satisfactory range of accuracy consistent with the intended purpose of the research application. Sensitivity analysis is a procedure that quantifies how adjustments in the model parameters change the values of the simulation results (Kocabas and Dragićevíć, 2006).

Parker *et al*. (2003) state that agent-based models fall into two classes: (1) theoretical "proof of concept" models for exploratory analysis, and (2) highly detailed empirical models for policy environments. The model presented in this thesis falls into the first category as a theoretical abstraction of social relationality so assessing its validity will be a challenge. This testing difficulty first relates to the fact that the relationality components are oversimplified representations of human communication so the possibility of disagreement between how people actually interact and cooperate and the manner in which this system simulates these processes is significant. Secondly, any ancilliary dataset that document the affective states, communication patterns, and cooperative dynamics is most likely a qualitative summary from a survey or questionnaire so validation of the behaviour of the model may be impractical. However, the issues of validation and verification must be addressed.

Refsgaard and Henriksen (2004) describe calibration as a procedure of adjusting the parameters of a model to reproduce the simulation outputs according to benchmark settings. The calibration of a model that simulates human behavior and interaction is particularly difficult, because there is often no data source against which the model can be fine-tuned. In the case of the theoretical community of social relationality, there is not necessarily a real world system to compare the simulation with. One avenue of calibration of this model is to compare the simulation outcomes to results from previous research on the N-Person's Prisoner's Dilemma and Trade Network Games. The authors of these studies have provided expert opinions of what will and should happen in socialization activities in their applications of a human system. The parameters for each component of this model should be set at the same initial values as in the original formalization to produce simulation results that should approximate the outcomes of these founding studies. For example, setting the non-employment payment to zero should lead to full labour market participation during each simulation time-step as recorded by Tesfatsion (1997) in runs of the Trade Network Game. However, the calibration process in this model will have to adjust many parameters to account for the influence of space on the functionality of these components. This is evident in the adjustment of the level of social welfare in a spatial labour market game as outlined in paper 3 of this thesis.

One of the main tests for gauging the trustworthiness of a model is through verification of the logic of its implementation as an abstract computer program. Kennedy *et al*. (2006) refer to verification as "programming the model right", which means that it is a sufficiently accurate representation of the real-world phenomenon for the purposes it is intended. Verification is done to ensure the model is programmed as error free as possible and that the algorithms and methods that drive the simulations are implemented properly. Minimally, it is a process including software debugging and evaluation testing runs to correct errors in an effort to ensure code consistency and integrity. The development of these models involved an iterative strategy of unit testing after each revision of the source code. As each of the components from the first four papers was introduced into the integrated model, the evaluation involved tracing the source code in debug mode within Eclipse Integrated Development Environment, which "steps through" the code one line at a time to verify the functionality and logic of the system. Following this regime of debugging, a level of certainty was gained that the model processes are activated as the right time and occur in the manner intended. Model verification proceeded as more tests were performed, errors were identified, and corrections were made to the underlying model. The end result of verification is technically not a verified model, but rather a model that has passed all the verification tests (North and Macal, 2007).

Epstein and Axtell (1996) suggest that the quantitative verification of a model can be attained with the process of docking or model to model comparison. Docking involves the development of new software or utilization of an existing model to run the same coded routines and methods of the original system, and, keeping the data fixed, evaluate the similarities in the simulation results. The main idea is that model confidence is significantly improved when two model produce the same effective results, particularly if the models were developed independently and with different programming languages. Due to the considerable programmatic requirements to development a secondary mode, docking was not pursued as a method of verification in this research.

Inner validation is concerned with the integrity of the processes described in the model so its assessment purpose is similar to verification. Peréz *et al.* (2012) describe inner validation as a testing procedure that is concerned with how well the model represents the theory and processes that describe and define its functionality. One method of testing the inner validity involves comparing the results of several replications of a simulation with the only difference being the random seed (Xiang *et al.*, 2005). Inconsistencies in the results will signify concerns with the validity of some aspect of the model.

Model validation is an assessment procedure that determines the adequacy and accuracy of the model's computational framework in matching the real world system of interest. For model testing, validation is the crucial phase but, due to the stochastic and non-linear nature of complex adaptive systems, it is also the most problematic. The standard method of testing the performance of a model is outcome validation (Manson, 2001). Outcome validation is concerned with the "goodness of fit" of the results from the simulation runs and the empirical data collected for the real-world system, and quantifying the similarity between them with a statistical measurement of agreement, such as the Kappa value. The behaviour of the model is considered more valid and acceptable the higher the measurement of statistical similarity. However, it is important to note that models are abstractions of reality so their resultant behaviours can never totally and exactly match a real system. Peréz *et al*. (2012) suggest that the performance of a model should be measured with degrees of validation, because there could be processes in the model that performed well despite the global disagreement so there is some value in the model. Yet, many researchers (Fagerstorm, 1987; Mentis, 1988; Thagard, 1988; Oreskes *et al.*, 1994; Crooks *et al.*, 2008; Peréz *et al.*, 2012) argue that the outcome validation of an agent-based model of any social system is impractical and impossible.

Agent-based models are inherently non-linear and subject to stochastic fluctuations so each simulation run could produce different outcomes that are compared to the same empirical dataset. Some simulation results could approximate the validation data but others could be quite dissimilar. Batty and Torrens (2005) add to the argument by stressing that in recent years agent-based models have increased in diversity and richness of internal structures, and these complicated model structures are never likely to be validated against an atemporal data source. Caswell (1976) proposes that a theoretical model can only be conceptually validated by judging its value on its usefulness to the intended purpose. Manson and O'Sullivan (2006) suggest that evaluation is an appropriate alternative to validation of abstract models, and this requires the researcher to find ways of expressing the capabilities and limitations of his model. One approach is face validation where domain experts are asked whether the model behaves reasonably and is sufficiently accurate, and this is generally a visual appraisal of the output. Mandelbrot (1983) also comments on the qualitative evaluation of a model by determining if the spatial patterns of simulation runs from the model visually "look right". The evaluation of a model can also be garnered from peer review of the methodology presented, and these expert opinions combined with experience and theory can set the foundation for model evaluation (Batty and Torrens, 2005). These arguments set the possibility of conceptually validating the qualitative performance of this model by checking with experts in the associated fields of research (Becu *et al.*, 2003; David *et al.*, 2005). Several criteria that can be used are (Janssen and Ostrom, 2006):

1. Is the model plausible given the understanding of the processes?

2. Does the behavior of the model coincide with the knowledge and experiences of the relevant contributors to the research?
3. Can an understanding of why the model's performance is either good or unacceptable be achieved?

Once a model has been verified, a series of simulation runs is carried out to test the sensitivity of the model by changing input parameters to determine the effect upon the model and its output. Sensitivity analysis investigates the logic behind the design of the internal structure of the model, and provides an understanding of the implications of each assumption in the development and running of the model. The basis of all social relations in this model is the concept of a geographic neighbourhood, the size of which determines the number of agents involved in the localized social interactions. To test the influence of neighbourhood size on the emergence of cooperation in social interactions, simulations with neighbourhood sizes ranging from 10 to 500 meters radius were run. For the smallest sizes, those less than 40 meters, the composition of the social grouping consists of an agent's immediate neighbours. However, an issue in several of the simulation using small neighbourhoods was that the groupings only contained a pair of agents, and in a group of $n \leq 2$ individuals, the N-Person's Prisoner's Dilemma can not be simulated. In contract, social interactions in neighbourhoods of greater than 300 meters radius led to increasing instances of defection as the agents were less fearful of retaliation for their selfish behaviours. The highest instances of localized cooperation and global social identity were evidenced for neighbourhoods within the 60 to 110 meter range, but the optimal neighbourhood size depends on the vector geometry of the spatial layer representing the buildings where agents can be situated.

4.0 Research Organization

This research is divided into five papers submitted to peer-reviewed journals. Each concentrates on one aspect or component of the general model.

Paper one discusses the theory and formalization of N-Person Prisoner's Dilemma social interactions in a spatial environment. The model architecture consists of a simulation module tightly coupled to a Geographic Information System. Space is paramount in the mobility dynamics of the citizens and the configuration and size of the interaction neighbourhoods. The concepts and influences of context preservation and neighbourhood depth are introduced in these initial sets of simulation runs. This article has been published in the Journal of Artificial Societies and Social Simulations, 12(18), http://jasss.soc.surrey.ac.uk /12/1/8.html.

Paper two presents a layered model of affect, the psychology component that provides each agent with a personality, mood, and emotional state. The theory of the N-Person Prisoner's Dilemma is modified to consider the affective states of the citizens in their behaviours before and after their responses to the outcomes of social exchanges. This article has been submitted for peer review in the Journal of Mathematical Sociology May 2013.

The third paper concentrates on the labour market dynamics within the socio-geographic community. The design of a spatial labour market game is based on the preferential partnerships between directed employee-firm pairings from a Gale Shapley matching process, and the simulation of labour market exchanges as Iterative Prisoner's Dilemma games. After the labour market transactions, the action strategies of a pair of successful agents in a neighbourhood are imported into an evolutionary learning module to produce an optimized behavorial strategy that is imitated by the lowest paid individual. This article has been submitted for peer review in the Journal of Computational Economics July 2013.

A conceptual formalization of emergent leadership and cooperation is the theme of the fourth paper. A literature review shows the entanglement of adaptive and administrative leadership provides the necessary tensions in the nonlinear social exchanges of the citizens for cooperation to emerge and set the topology for localized and environment wide leadership. The importance of the diffusion of knowledge and opinions throughout the environment as a factor in emergent cooperation and the supplementary facilitation of the social interactions is discussed. A working model of self-organizing leadership requires a two stage plan of first presenting the theory behind the formalization and then the programming of the complicated integration of the components that simulate the processes of social relationality and cooperation. The development and implementation of a working model of emergent leadership is beyond the scope of this thesis so this paper is limited to the proposal of an abstract formalization. This article has been submitted for peer review in the Journal of Leadership Quarterly June 2013.

Paper five is the integrated model consisting of all of the components of the previous papers. This is a spatially explicit model containing the spatial, social, psychological, and labour market elements of a well-connected community. The modeling environment consists of affective citizens engaged in Prisoner's Dilemma game play after they have relocated to the activity site. For a socio-geographic environment, a steady state of cooperation is conditioned on the perpetual social mimicry of successful action strategies to a point where a small set of schemas prevail, and the altruistic tendencies of a majority of the agent population. This article has been submitted for peer review in the Computers, Environment, and Urban Systems June 2013.

A concluding chapter summarizes the methodologies for each the components of the model, list the achievements of the research, and proposes considerations for future work.

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Part II: Papers

6.0 A Spatial Agent-Based Model of N-Person Prisoner's Dilemma Cooperation in a Socio-Geographic Community.

Abstract

The purpose of this paper is to present a spatial agent-based model of N-person prisoner's dilemma that is designed to simulate the collective communication and cooperation within a socio-geographic community. Based on a tight coupling of REPAST and a vector Geographic Information System, the model simulates the emergence of cooperation from the mobility behaviors and interaction strategies of citizen agents. To approximate human behavior, the agents are set as stochastic learning automata with Pavlovian personalities and attitudes. A review of the theory of the standard prisoner's dilemma, the iterated prisoner's dilemma, and the N-person prisoner's dilemma is given as well as an overview of the generic architecture of the agent-based model. The capabilities of the spatial N-person prisoner's dilemma component are demonstrated with several scenario simulation runs for varied initial cooperation percentages and mobility dynamics. Experimental results revealed that agent mobility and context preservation bring qualitatively different effects to the evolution of cooperative behavior in an analyzed spatial environment.

6.1 Introduction

The evolutionary processes that are fundamental to cooperation in social situations have been an enduring theoretical problem in biological, sociological, and geographical research. Cooperation is behavior that may initially cost a person or group but ultimately benefits other individuals or social assemblages. While this may seem an uncomplicated concept, the derivation of satisfactory theoretical explanations for real-world altruistic behavior has been a challenge (Killingback and Doebeli 2002). However, the prisoner's dilemma has become one of the most widely adopted methodologies for studying the evolution of cooperation in simulated social environments.

Most of the published work about the prisoner's dilemma deals with the two-player iterated game. These articles show how the repeated interactions between pairs of players can result in the emergence of cooperation due to reciprocal altruism. Beginning with Axelrod (1984), iterated prisoner's dilemma tournaments have been run to compare and identify the evolutionary strategies that consistently produce the best cooperation results. The more successful strategies have demonstrated that spatial structure is an influential factor in building cooperation. Nowak and May (1992) presented the seminal work that showed how the spatial effects of the interactions between simple agents in a cellular automata (CA) model of the iterated prisoner's dilemma was sufficient enough for the evolution of cooperation. Alonso et al. (2006) devised a similar CA model that simulated cooperation through the behavioral adaptation of Pavlovian agents as they adjusted their cooperation by mimicking the most successful player in a neighbourhood.

N-person prisoner's dilemma (NPPD) has also been a research topic of spatial modelers who are interested in the emergence of collective cooperation in social groupings. Referred to as a social dilemma situation, a player has to choose between his own interests or exhibit cooperative behaviors that benefit the grouping of *N* players. Akimov and Soutchanski (1994) developed a spatial NPPD game to relate how collective cooperation depends on the behavioral patterns of simple automata within a CA. Szilagyi (2003) presented a CA model of NPPD based on the interactions of irrational agents in a social unit and revealed how the chaos like actions of the agents was an important condition for decentralized group cooperation. Zhao et al. (2005) expanded the work of Szilagyi (2003) and proposed an N-person model that establishes a continuous state of cooperation from the attitudes and personality types of agents in a CA. They found that the depth of the neighbourhood of the social groupings was the central factor that determined cooperation dynamics in the simulation runs. This point raises an important condition of a prisoner's dilemma CA in that the automata are usually fixed entities in a regular lattice of cells. Context preservation has been established as a key factor in the evolution of cooperation and is intuitively linked to the neighbourhood and mobility rules within the spatial model. However, there is minimal published research that deals with the spatial modeling of NPPD involving mobile agents.

In this paper, it is argued that a spatial agent-based model of N-person prisoner's dilemma can extend the study of collective communication and cooperation within a socio-geographic community. Based on a tight-coupling of REPAST and a vector Geographic Information System (GIS), the model is designed to simulate the emergence of communal cooperation relative to the mobility behaviors and interaction strategies of citizen automata. Support for the methodology is demonstrated with simulation runs for a real-world analyzed environment and a discussion of its use in simulating scenarios of social dynamics.

6.2 Agent-Based Models

Agent-based models (ABM) are comprised of a community of agents, an agent being an autonomous entity that is able to act locally in response to stimuli from the environment, to communicate with other agents, and to have goals that it aims to satisfy. Community relates to the relationship between individual agents in the system, and these could be either reactive or cooperative (Benenson and Torrens 2004).

The goal of agent-based models of social systems is to enrich the understanding of the fundamental processes that may appear in the environment. This requires the modeling of the essential characteristics and attributes of the agents, the simple rules of agent interaction, and the emergent patterns of automata communication and interactions. Communication is one of the most important characteristics necessary for agent interactions and is the basis for the emergence of negotiation, collective behaviors, and social cooperation.

6.3 Prisoner's Dilemma and Social Cooperation

Many studies in the social and computer sciences have utilized the prisoner's dilemma to analyze the emergence of cooperation among non-relatives in social environments (Brembs 1996; Trivers 1971; Axelrod 1984). The popularity of the prisoner's dilemma stems from it being a robust and fundamental method of modeling the emergent social structures from the reciprocity of cooperative actions from members of social and biological communities (Cohen et al. 1998). Furthermore, the game is appealing from its simplicity of statement and design and its applicability to agent-based simulations of leadership, cooperation, and social differentiation from the interactions between neighbouring agents.

6.3.1 Prisoner's Dilemma

Originating within the field of game theory, the prisoner's dilemma (PD) is a type of non-zero sum game played by two players who can choose between two moves, either to cooperate with or defect from the other player. The problem is called the prisoner's dilemma, because it is an abstraction of the situation felt by a prisoner who can either cut a deal with the police and tell on his partner (defect) or keep silent and therefore tell nothing of the crime (cooperate). The key tenet of this game is that the only concern of each individual player is to maximize his payoff during the interaction, which sets the players as naturally selfish individuals. The dilemma arises when a selfish player realizes that he cannot make a good choice without knowing what the other one will do. Non-zero sum is a situation where the winnings of one player are not necessarily the losses of the other. As such, the best strategy for a given player is often the one that increases the payoff to the other player as well.

Table 6.1 highlights the structure of a canonical payoff matrix used in a PD game.

Table 6.1: Payoff Matrix for a General Prisoner's Dilemma Game

		Player A	
		Cooperate	Defect
Player B	Cooperate	R, R	S, T
	Defect	T, S	P, P

R is the reward payoff that each player receives if they both cooperate, P is the punishment that each receives if both defect, T is the temptation to defect alone, and S is the sucker payoff that is assigned when a player cooperates alone. The payoff structure is such that T>R>P>S, which ensures that there's always the temptation to defect since the gain for mutual cooperation is less than the gain for one player defection.

McCain (2003) states that the premise of a PD game is the strict domination of cooperation by defection so that the only possible equilibrium is obtained when all players defect. However, the pursuit of selfish interests will not produce a collective order required for the functioning of a social system. Some form of prisoners dilemma is therefore needed for the modeling the dynamics of a social community.

While it has been extensively modeled, researchers have dismissed the basic PD as an unrealistic abstraction of individual interactions. Firstly, PD is intended to study finite two person interactions, but real-world social communities can consist of long-term many-person interactions. Secondly, it is assumed that there is no communication between the two players and no history of past exchanges. Prior knowledge of past interactions may commit the players to coordinated strategies of cooperation. Lastly, the players are assumed to be rational, which implies that both will continually decide to defect to maximize their individual payoffs and never cooperate.

Nevertheless, researchers have expanded the standard PD game to enable participants to play the game multiple times and to have knowledge of previous moves. The iterated prisoner's dilemma has demonstrated that the players' decision to cooperate or defect accumulates over time as each player develops a reputation that affects the incentive of others to cooperate.

6.3.2 Iterated Prisoner's Dilemma

Axelrod (1984) presents an extension to the classical prisoner's dilemma scenario that permits players to repeatedly choose mutual strategies and have memories of their previous encounters. A strategy in a repeated game is a decision rule that specifies the probability of cooperation or defection for a player given some history of interactions against a particular opponent. For example, an agent that adopts the strategy ALLC (all cooperate) will always cooperate with the opponent, regardless of past interactions and expected payoffs.

During iterative prisoner's dilemma (IPD) play, two participants will play several consecutive iterations of the game using a payoff matrix (see Table 6.2) to accumulate a total score. The player with the larger cumulative score is deemed the winner and influences the cooperation strategy of the opponent.

Table 6.2: Payoff Matrix for an Example Iterated Prisoner's Dilemma Game

		Player A	
		Cooperate	Defect
Player B	Cooperate	3, 3	0, 5
	Defect	5, 0	1, 1

Through iterative play, cooperative and non-cooperative behavior will typically be reciprocated to a certain extent. Trivers (1971) describes how reciprocal altruism usually occurs through repeated interactions with the same individuals where a player returns the loyalty to an opponent who has previously cooperated.

Several researchers (Axelrod 1984; Boyd and Lorderbaum 1987; Nowak and Sigmund 1992) organized computer tournaments to detect strategies that would favor cooperation among individuals engaged in IPD. The goal of these contests is to pit different computer strategies against each other to identify ones that had the highest scores or instances of cooperation. Axelrod (1984) was one of the first to coordinate an IPD tournament, a round robin competition between fifteen deterministic strategies. The simplest strategy, Tit-For-Tat (TFT), was determined the best; cooperate on the first move and mimic the opponent's move for all subsequent moves. Altruistic strategies tended to outperform the greedy methods over the long-term.

An important finding of the competitions is that context preservation was determined to be a crucial factor for sustaining cooperation for interaction processes (Cohen et al. 1998). The emergence and maintenance of cooperation often depend on conditions that preserve the neighborhood of the interacting players. In addition, context preservation increases the likelihood of local influencing (the tendency of players who interact frequently to become more similar over time) and homophily (the tendency to interact more frequently with the same individuals).

Stochastic strategies have also been used in IPD tournaments. Nowak and Sigmund (1992, 1993) revised the simulations of Axelrod (1984) to model cooperation in noisy environments. They argue that it is possible that the actions of a player may be misinterpretations due to random errors, thus leading to a sequence of unwarranted punishment or cooperation. Running the competition with a variety of stochastic strategies, such as Pavlov, it was shown that cooperation could emerge as long as a stochastic version of TFT is included. This highlights the importance of a minimal social structure required for evolution of cooperation (Eckert et al. 2005).

Critics have questioned the ability of IPD to simulate real world problems because of its structure as a two-person game (Yao and Darwen 1994). Many social and economic problems require analysis of group dynamics, and the strategies that work well for individuals in the IPD fail in large groups. For example, a two-person strategy that is predicated on the self interest of a single individual is not designed to model the emergence of cooperation from collective behaviors. The n-person prisoner's dilemma is a more realistic and general game to model real-life social problems.

6.3.3 N-Person Prisoner's Dilemma

N-person prisoner's dilemma (NPPD) models have been referred to as social dilemma games, because they are focused on the simulation of the collective actions and behaviors in social groups (Schelling 1973). Harden (1968) describes NPPD as a "tragedy of the commons" game in which the players are worse acting according to their self interests than if they were cooperating and coordinating their actions. During play, individual players may cooperate with each other for the collective good of their social environment, or they may prefer to pursue their selfish interests. The incentives to cooperate may depend on how many players are contributing to the group and the effect of their actions. In multi-player interactions, cooperation and social cohesion emerge from the consensus behaviors and actions of the social unit even though the preferred course of action for an individual player is still defection.

A typical social dilemma can be considered an n-person game ($n \geq 2$), in which each player has the same preferred option that does not change regardless of the actions of the other players. Every player has the same payoff structure and can choose to either cooperate, C, or defect, D. The payoff of each player that defects is represented as D(m), where m is the number of players in a social grouping that cooperate ($0 \leq m \leq n-1$). The payoff for each cooperating player is donated as C(m). The social dilemma game is then defined by the following conditions (Akimov and Soutchanski 1994):

1. $D(m) > C(m + 1)$: each player is better off choosing to defect rather than cooperate, regardless of how many players choose to cooperate on a particular play of the game.
2. $C(n) > D(0)$; if everyone cooperates, each player is better off if everyone defects.
3. $D(m + 1) > D(m)$ and $C(m + 1) > C(m)$; the more players cooperate, the better off each player is, regardless of whether he chooses to cooperate or defect.
4. $(m + 1)C(m + 1) + (n - m - 1)D(m + 1) > mc(m) + (N - m)D(m)$; society as a whole is better off the more players cooperate.

Figure 6.1 is a graphical representation of an example situation that shows the payoff functions for a player that chooses the preferred defection option (P) or the un-preferred cooperation (U) alternative, depending on the number of other players (0 to n) that choose U. To illustrate, at $x = n/3$, a third of the players choose to cooperate and two thirds defect: P_x and U_x are the payoffs to the player that chooses the defection (preferred) or cooperation (un-preferred) alternatives, respectively. The payoff functions in the NPPD are structured so that each player receives a higher payoff for defection than for cooperation (the P curve must always be above the U curve).

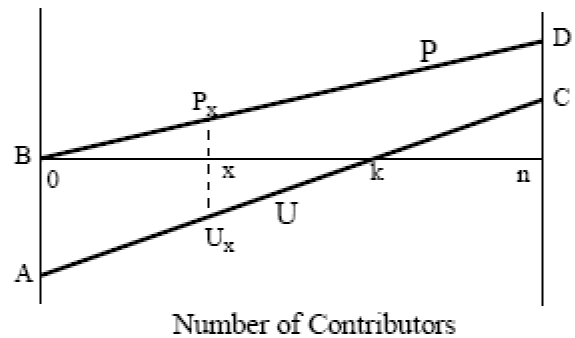

Figure 6.1: N-Person Prisoner's Dilemma Payoff Functions for Preferred Defection and Un-Preferred Cooperation, Relative to the Number of Other Players that Decide to Cooperate:
(from Akimov and Southchanski 1994)

It is important to note that an NPPD game is not an expanded version of the iterated pairwise interaction game. It is a true multiplayer game where each player simultaneously interacts with all of the other players in a social grouping and decides to either cooperate or defect according to the rewards or punishments derived from the collective. A player's decision to cooperate or defect is therefore dependent on the number of cooperators and defectors in his neighbourhood and the utility of the payoff functions at each time step of the play sequence.

While not as numerous in the literature as the two-person IPD, NPPD simulations have been presented as agent based models. The sequencing of these simulations depends on the components and parameters of the ABM. First of all, the initial probabilities of cooperation and actions of each individual in the social environment are assigned, often randomly, according to user-defined instance parameters. Secondly, the neighbourhood configuration of the social grouping is determined. This can range from a grouping of socially similar players, a spatially defined interaction region, such as a Moore neighbourhood in a cellular automata, or the entire social environment itself. Next, the interaction strategies and the payoff and updating schemes dictate the course of the game play. Many different types of strategies have been tested in NPPD games, but most are deterministic strategies based on the probability distribution for the two possible actions and the history of player interactions among the social group (Kehagias 1994). Payoff functions similar to figure 6.1 determine the reward/penalty assigned to each player dependent on the number of cooperators and defectors within the neighbourhood. The appeal of this type of model for simulating cooperation for real-world applications is the capability of setting the players as probabilistic learning automata so that their behaviors are learned and adjusted throughout the simulation. In this manner, behavior refers to how an agent decides to act based on his current state, the reward/penalty from previous actions, and the actions and states of the neighbours. Szilagyi (2003) makes the compelling argument that human behavior is best described as stochastic but influenced by personality characteristics. His work investigates the role of personalities in stochastic learning automata in the multiplayer PD game. Stochastic learning automata are agents whose behavior is influenced by random perturbances to simulate noise or stochastic responses from the environment. Assigning personalities to the agents imitates human decision-making and presents a method of specifying the updating schemes from certain attitude states and personal influences (Zhao et al. 2005). Therefore, agents with different personalities can be assigned different updating schemes and allowed to interact with each other, resulting in observations of how the various personality types respond to one another in the same social environment. A variety of personalities, such as Pavlov, conformist, and greedy (Brembs 1996), have been applied in NPPD games, the specifics of each will be discussed later. Some of the updating schemes of the agents used in NPPD games have been implemented as utility functions, probabilistic equations, and choice heuristic decision rules (Axelrod 1997). The updating schemes adjust the probabilities of the agent's actions by the reward/penalty received from the environment based on his and the other players' behaviors and attitudes. The actions of the participating agents as they make repeated decisions and interactions will determine the degree of cooperation that occurs within a social unit.

The N-person prisoner's dilemma game seems well suited for realistic albeit simple investigations of collective behaviors within a social system and can be the foundation for a spatial agent based model of cooperation within a socio-geographic community.

6.4 Spatial Agent Based Modeling of N-Person Prisoner's Dilemma Cooperation

The development of a spatial agent-based model of NPPD is contingent on the processes that define a socio-geographic community. From a research perspective, a socio-geographic community is both a geographical object and a sociological subject. Firstly, it is an integrated geographic network of social units defined by the interaction patterns and citizen flows throughout a dynamic area of collective social, economic, and emotional actions. Flow refers to labour market dynamics, individual flows to access goods and services, daily commuting activities, etc. As a sociological subject, a community codifies norms and behaviors to control the processes of social and institutional interactions (Loomis 1996). The community becomes a social system of local communication and actions involving a collective identity, solidarity, and collaborative efforts. As a cohesive object and subject, the simulation of a real world community involves agents with personalities and attitudes that communicate and move throughout the environment as part of their daily activities. Formally, the model must specify the social unit as an analyzed environment and the citizen agents as analyzed automata. Analyzed agents are automata that mimic real world entities based on empirical data, and the analyzed environment is a real world location (Couclelis 2001).

This section of the paper presents the development of a conceptual spatial agent-based model of citizen cooperation within a socio-geographic community. Each citizen agent is designed with reference to the spatial structure of the analyzed environment, states variables relevant to the application, state transition rules, movement rules, neighbourhood calculation, and the NPPD game play. Before these components are discussed, an overview of the basic architecture of the generic model is given.

6.5 The Architecture of the Generic Model

The generic model is developed as an exploratory approach for simulating the trends and patterns of citizen automata in social groupings. Generic infers that the model is applicable to multiple socio-geographic environments and contains functionality that is fundamental for any given social system. Also, the parameters of the model are set with user-defined variables that characterize the simulation scenario.

The model is designed as a modeling-centric system with embedded vector Geographic Information System (GIS) capabilities (see figure 6.2). Formally, the tight coupling of agent-based modeling and GIS functionality create an identity relationship between an agent and its spatial feature (Brown et al. 2005). The agent-based modeling platform was developed with REPAST (Recursive Porous Agent Simulation Toolbox) Java to simulate agent interactions, movements, and the NPPD game play.

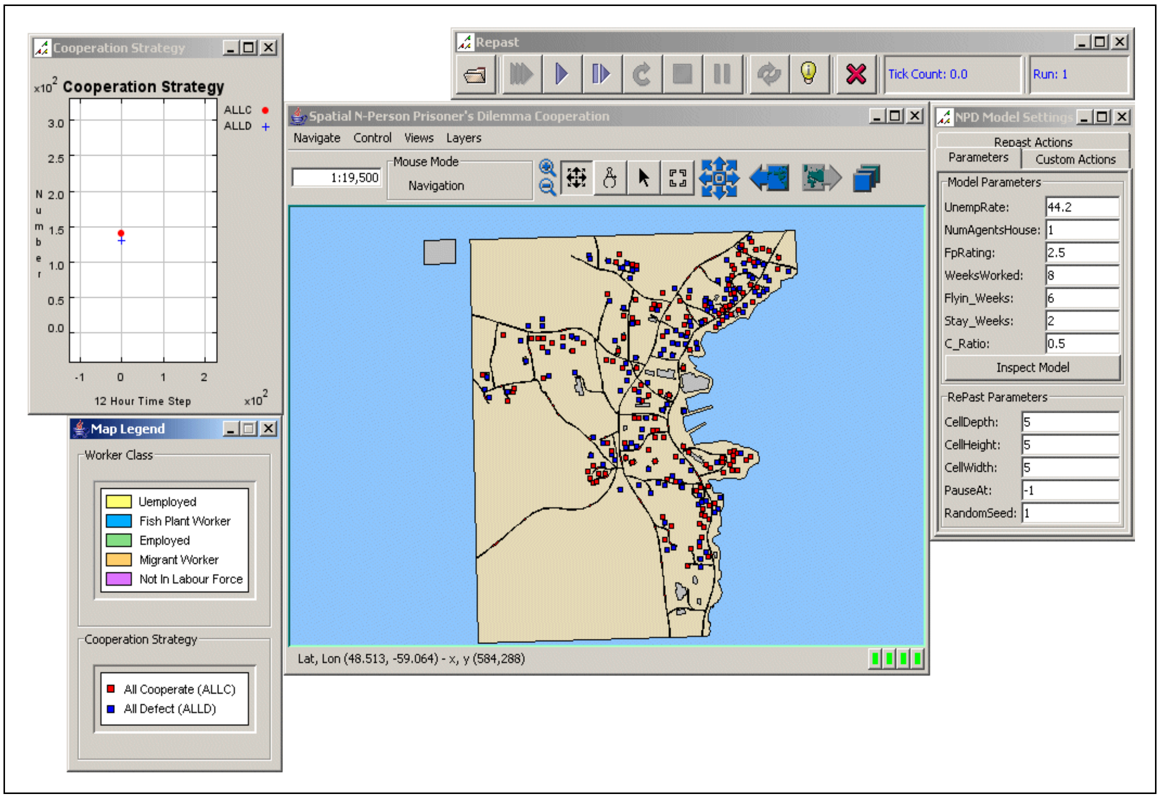

Figure 6.2: Interface of the Spatial Agent-Based Model of NPPD Cooperation

Within this component, agents are object-oriented entities that use their states and definitions to simulate behaviors. The agent based methods model the behavior of the agents and alter their states, which are stored as geographic features within the GIS as polygons and points. GIS operations are implemented with a number of software libraries that are imported into the simulation toolbox. Specifically, Java Topology Suite (2007) is utilized to calculate topology and neighbourhood configurations, GeoTools (2008) provides data importation and exportation, and OpenMap GIS (2007) is used for attribute querying and map visualization. As a further enhancement, the sequential line graphing and movie creation methods within Repast are used to record changes during simulation runs.

6.6 Spatial Structure of Agent Locations in an Analyzed Environment

An analyzed environment is a real world study area that is set as the spatial confluence region for the simulation runs. The entities required for the simulation of cooperation in a socio-geographic community are fixed non-mobile building automata, specifically resident households, businesses, community services, and schools, and non-fixed mobile citizen agents. The modeling configuration is set to the town of Catalina, Newfoundland and Labrador, Canada (figure 6.3) because of the availability of satellite imagery and, more importantly, individual level socio-economic statistics to microsynthesize and assign state variables to each citizen agent. Locations of both types of agents follow a vector GIS geo-referencing convention. The building entities are first derived from an imported ESRI© shapefile that was digitized from the satellite imagery. Since they are fixed automata, the buildings are directly registered as two dimensional polygon objects with coordinate lists and topology within the GIS component. The citizen agents are also directly registered during initialization, but are locationally pointed during movement events. At initialization, the household locations of a user-defined number of citizens are set as

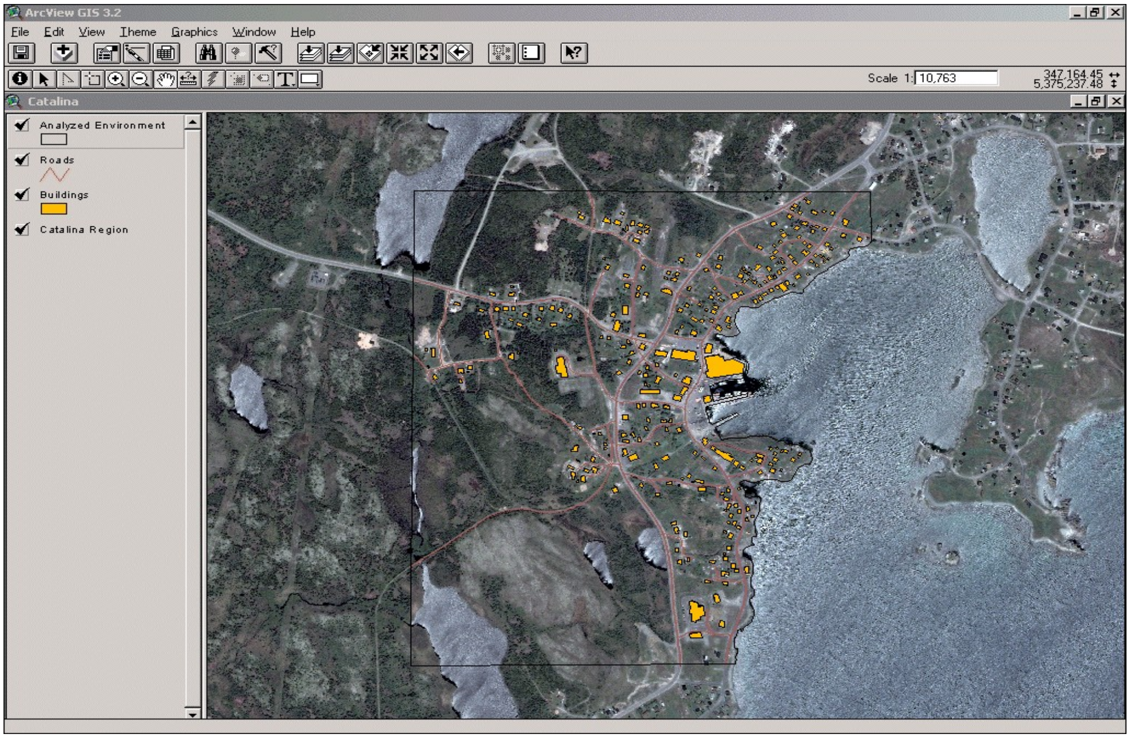

Figure 6.3: Analyzed Environment of Central Catalina, Newfoundland and Labrador, Canada

the geographic coordinates of the centroids of randomly selected building polygons. This produced a set of citizen point objects that are directly geo-referenced to their assigned household locations. The relationship between both types of entities is hierarchical such that the point citizen agents are spatially nested within the building automata. As a citizen moves, the destination location is geo-referenced by pointing to a specific building object. For example, the destination for citizen agent A at time *t+1* could be a school, whose locational coordinates are stored and easily accessible from the GIS database. Locational pointing is convenient for mobile agents because their locations can be constantly varied and reset as the simulation proceeds.

6.7 State Variables and State Transition Rules

State variables are the characteristics of the fixed and mobile entities that are inputted into the transition rules to determine their behaviors. The buildings have a single state variable according to their previously determined type: household, business, public service, or school.

The citizen agents are specified with state variables that determine their mobility behavior and their initial action choice for the NPPD game play. Each point agent is initialized with an age, gender, education level, and worker type (unemployed, fish plant worker, migrant worker, other, or not in labour force). These variables were estimated from selected population and occupation tables from the 2006 general census release from Statistics Canada. During the setup sequence of a simulation run, the population and occupation data is entered into a set of initialization equations to randomly compute or assign the states to each citizen agent.

State transition rules are currently only applicable to the citizen agents and consist of two sets of heuristics: those relating to the probability of cooperative action and rules that are relevant to the simple demographic profile of the citizens. The demographic rules are concerned with increasing the age of each citizen by a factor of 1 for each yearly equivalent of time steps and altering the worker type according to a random updating event. Throughout the simulation run, the model can implement a worker turnover ratio to randomly change the worker type attribute of citizen agents between the ages of 15 to 65. A change in the worker type of an agent can affect its mobility behavior.

6.8 Movement Rules

The object-oriented framework of REPAST coordinates movement as discrete event simulations, in which a scheduling mechanism directs the sequencing of agents' mobility behaviors (Zeigler et al. 2000). In this model, movement rules manage both short-term migration (fly-in/fly-out employment) events and daily commuting activities of the citizen agents. Both types of mobility are scheduled in a asynchronous manner, where the agents' move between a pair of origin and destination locations at a specified time step. Each time step represents a 12-hour interval and two consecutive time steps a typical day. The destination for a movement event is based on the worker type of each agent, where it is assumed that he is most likely to travel to and from his household to the site of his particular occupation. For example, a school is the most probable destination for a teacher and children aged 5 to 18 during the weekday period. P_{exp} is the probability that a citizen moves to the expected site and is arbitrarily set at 0.9. However, a stochastic perturbance value is computed for each destination choice to model the nonlinearities of human decision-making, where a person often fails to make the obvious choice. A random number generator class in REPAST computes a perturbance value, P_{stoc}, between 0 and 1 to determine whether an agent moves to another business or service location or whether he stays at his residence for that particular time step. When $P_{stoc} > P_{exp}$, a destination option is randomly selected from all relevant buildings, except the usual place of work and other agent households, and a motion rule relocates the citizen to this new position for this sequence.

The fly-in/fly-out workers are an increasing familiar subcommunity of individuals in communities throughout Newfoundland and Labrador. These are workers who are employed for weeks in locations outside of the community of residence. Even though these workers are frequently detached from their home communities, they are still an important and influential socio-economic unit within the broader community network. Fly-in/fly-out employment is a work pattern consisting of both an outmigration and immigration event. During model setup, each migrant worker is randomly assigned a start date of his first migration event, and a pair of scheduled basic action rules are initialized to implement the outmigration and immigration events. Outmigration is a scheduled action of placing a migrant worker agent in a virtual migration container for a user-defined period of time (see Flyin_Weeks variable on right side of figure 6.2) and immigration is a scheduled action that returns a migrant worker to his household for a user-defined stay period (Stay_Weeks variable on figure 6.2). This sequential movement continues throughout the entire simulation.

Mobility behavior is an important element in the spatial agent-based simulation of cooperation in a social environment, because it sets the neighbourhood configuration for the prisoner's dilemma game play.

6.9 Interaction Neighbourhoods

An interaction neighbourhood defines the extents of the spatial association of a social grouping within the environment. The rule set for neighbourhood delineation is based on the proximity of citizen agents on a geometric network, where agents within a specified straight-line distance of each other are considered neighbours. At each time step, the topology and automata composition of the neighbourhood for each citizen agent is estimated with a GIS buffer operation. Formally, a buffer, or enclosing circle, of a user-defined radius is drawn around the point location of each agent, and a point-in-polygon method identifies those agents that fall within the buffered area and classifies them as neighbours. For example, the citizen points symbolized in yellow in figure 6.4 are the neighbours situated within a 70-meter radius of agent A. With the neighbourhood defined, an arraylist of agent objects including the identified neighbours and the citizen of interest is passed to the agent-based model to begin the NPPD game.

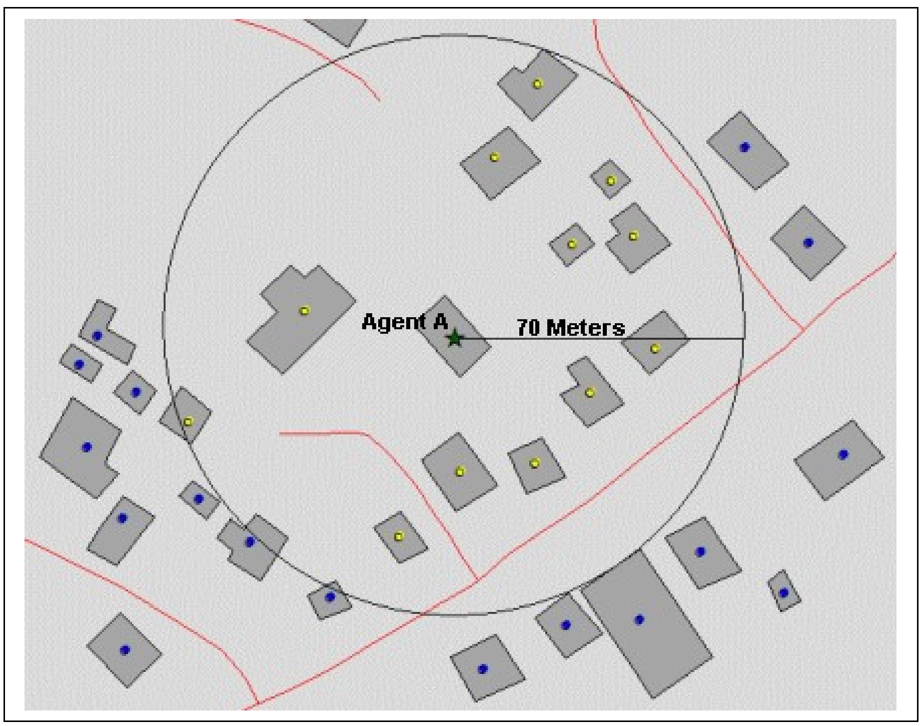

Figure 6.4: Configuration of a 70 Meter Neighbourhood Buffer of Agent A

An interesting consideration for the simulation of agent cooperation is the effect that movement has on the calculation of neighbourhoods. Each time an agent moves, it necessitates the generation of a new neighbourhood configuration and produces a different listing of neighbours. Recall that for the two-person IPD, context preservation was a crucial element for the emergence of cooperation. It is assumed that context preservation will be a factor for the worker agents while they are at their place of work, because the calculated neighbourhood will be a compact grouping of social agents with a shared interaction history and similar state variable values. It is possible that a degree of social cohesion will arise amongst these agents and that they will be more inclined to cooperate with each other during the social dilemma simulation.

6.10 Spatial N-Person Prisoner's Dilemma

The aim of a spatial NPPD game is to investigate social interaction behaviors and communication between people situated in a stochastic environment. As Szilagyi (2003) corrects surmises, human behavior cannot be accurately simulated with rational agents, because biological objects rarely act rationally. As a result, several researchers (Boone et al. 1999; Szilagyi and Szilagyi 2002; Zhao et al. 2005) have stressed the need to investigate the role of personalities in the prisoner's dilemma and to set the agents in the model as stochastic learning automata. These considerations were central to the development of the NPPD component in this model.

6.10.1 Basic Definition

Each citizen agent is a stochastic learning entity with a predetermined personality type and cooperation action. In a neighbourhood of N agents, the state of each citizen at time t is characterized by 0 (defection) or 1 (cooperation). During an interaction event, agents take actions according to the probabilities updated on the basis of the reward/penalty received for previous actions, their neighbours' actions, and their personalities. The updating sequence occurs synchronously for all of the agents in the neighbourhood or social grouping.

6.10.2 Components and Parameters of the N-Person Prisoner's Dilemma

As a generic game, constraint parameters are set by the user to facilitate the NPPD simulation and to initialize the agents' states. First, the percentage of the total number of agents, C_x, that begin the simulation as cooperators is included. Next, a set of initialization rules in the setup methods of REPAST uses C_x to randomly set each agent as either a cooperator or defector and initialize both its individual probability of cooperation and defection.

At each time step, the model calculates the neighbourhood of each agent and determines the total number of cooperators and defectors in that grouping. The interaction proceeds as the reward/penalty for each agent is computed from a set of payoff functions. Lastly, each agent updates their cooperation action on the basis of the reward/penalty computed from the payoff functions and the influence of its personality. In modeling terms, personalities are the interaction strategies that agents employ during game play. Zhao et al. (2005) lists several of the personality profiles and strategies that have been used in NPPD simulations:

1. Pavlovian: an agent with a coefficient of learning whose probability of cooperation changes by an amount proportional to the reward/penalty it receives from the environment
2. Stochastically predictable: an agent whose probability of cooperation is constant but fluctuates with periodic random perturbances. For example, an angry agent ($p=0$) always defects.
3. Accountant: an agent whose probability of cooperation depends on the average reward for the social grouping for a previous action.
4. Conformist: an agent who imitates the action of the majority in the social unit.
5. Greedy: an agent who imitates the neighbour with the highest reward.

These personality types represent certain simple aspects of actual human behavior. Szilagyi and Szilagyi (2002) state that Pavlovian agents are the most realistic automata for the investigation of the evolution of cooperation, because they are simple enough to know nothing about their rational choices but intelligent enough to follow Thorndike's (1911) Law of Conditioning. Specifically, an action that produces a satisfactory state of affairs tends to reinforce the repetition of that particular action. Therefore, the citizen agents in this model are set as Pavlovian automata, and the interaction functions are specified to support this condition.

Figure 6.5 shows the payoff curves for the cooperators and defectors, and, as required, the D curve is above the C curve so it is always best for an agent to choose to defect. Note that the payoff of an agent depends on its previous action (C or D), the ratio of cooperators to the total agents, and a stochastic factor added to the environment. The payoff curves for both the defectors and cooperators are straight lines functions expressed
as (Szilagyi, 2003):

$$D = -0.5 + 2x \tag{6.1}$$

$$C = -1 + 2x \tag{6.2}$$

The stochastic factor is a parameter that accounts for any uncertainty in the agent interactions and noise in the environment. This is applied to the payoff functions to thicken each line to produce a range of payoffs for a cooperation ratio. For example, an agent with previous action C in a neighbourhood with 0.60 cooperation receives a payoff reward of 0.207 ± 0.033. In a deterministic environment where the stochastic factor is zero, the payoff reward would be 0.207.

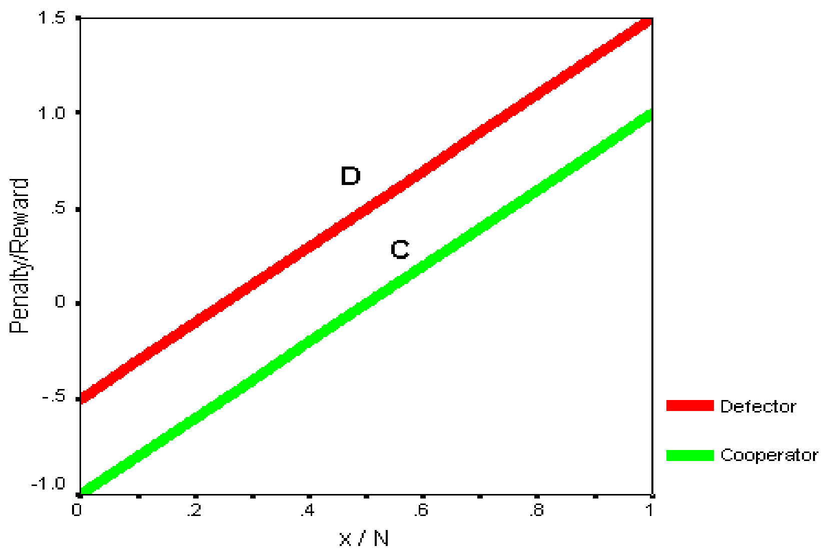

Figure 6.5: Reward/Penalty Payoff Functions for Pavlovian Defectors and Cooperators (from Szilagyi 2003)

The updating scheme is a set of functions that assign an action to a citizen agent probabilistically based on his behavior and the behaviors of the collective. Let $p_i(t)$ be the probability of cooperation for agent *i* at time *t*, and $q_i(t)$ the probability of defection for agent *i* at time *t.* At each iteration, agent *i* changes $p_i(t)$ and $q_i(t)$ according to the reward/penalty received from the environment's responses. For instance, at time *t*, the agent chooses C and the payoff functions reward it, then the probability of choosing C is increased for subsequent time steps. Each agent is also assigned a coefficient of learning $\alpha_{i,}$ where $0 < \alpha_i < 1$, to adjust the probability according the neighbourhood responses. α_i increases if an agent makes repeated actions within the environment but decreases as the actions become varied. Hence, the probability of cooperation for agent *i* at time *t+1* is:

$p(t+1) = p(t) + (1-p(t)) * \alpha_{i,}$ if at time *t*, action = C and the payoff = reward (6.3)

$p(t+1) = (1-\alpha_i) * p(t)$, if at time *t*, action = C and the payoff = punishment (6.4)

Note that for every t there must be $q(t) = 1 - p(t)$. The same set of equations is also used for updating the action probabilities when the previous action is D:

$$q(t+1) = q(t) + (1-q(t)) * \alpha_i, \text{ if at time } t, \text{ action} = \text{D and the payoff} = \text{reward} \quad (6.5)$$
$$q(t+1) = (1-\alpha_i) * q(t), \text{ if at time } t, \text{ action} = \text{D, and the payoff} = \text{punishment} \quad (6.6)$$

The state of agent i is updated contingent on its previous state, a neighbourhood production function, and the probabilities for both C and D. The neighbourhood production function is the average cooperation payoff for the group computed as:

$$\text{pf} = \sum C_j / n \,, \quad (6.7)$$

where C_j is the number of cooperators and N is the total number of agents in the neighbourhood.

Thus, the state of agent i at time $t+1$ with $S(t)$:

For $S(t) = C$:

$$S(t+1) = \left\{ \frac{\text{D, if payoff for agent i} < \text{pf}, p(t+1) < q(t+1), \text{and } q(t+1) > R_u}{\text{C, retain previous action if the conditions for D are not satisfied}} \right\} (6.8)$$

For $S(t) = D$:

$$S(t+1) = \left\{ \frac{\text{C, if payoff for agent i} < \text{pf}, q(t+1) < p(t+1), \text{and } p(t+1) > R_u}{\text{D, retain previous action if the conditions for C are not satisfied}} \right\} (6.9)$$

,where $R_u \in [0,1]$ is a uniform random value.

6.11 Results

The goal of the simulation scenarios is to test the ability of the system to model social cooperation in a spatial environment considering a number of fundamental considerations and questions. First of all, it is important to investigate the effect that the initial configuration of the model, which relies on the user-defined instance variables, has on the results of a spatial NPPD. Secondly, the emergence of cooperation in social groupings can depend on the context preservation of neighbourhoods so it is imperative to consider the effects of the mobility of the citizens on agent interactions. Lastly, a qualitative visual analysis of the resultant cooperation maps will identify any localized patterns of cooperation or defection and whether their emergence is due to agents' worker type and mobility status. For these purposes, separate sets of simulations were run with initialized proportions of 20% and 80% cooperators among the citizens and were repeated with both fixed and mobile citizen agents. To simulate the interaction of fixed citizen agents, their mobility rules are disabled, and they are restricted to their place of residence. The social community involves 271 citizen objects in an analyzed geographic environment that interacted and communicated for a full calendar year.

Figure 6.6 and 6.7 are the map and graph of the cooperation patterns for 20% cooperation and mobile agents respectively. The graph in figure 6.7 shows the proportion of cooperating agents in the social environment as a function of the number of iterations. Throughout the simulation period, the number of total cooperators fluctuated in an irregular manner so that there is never an extended period where there are a majority of cooperators in the environment. The intermingling of cooperators and defectors in the map of figure 6.6 shows that the clusters of C and D are small (see northeast corner of map) and subject to change at each iteration. It is suspected that the mobility of the agents and the changing in neighbourhood configuration effect the learning rate of the Pavlovian agents and cause them to continuously change cooperation actions. Figures 6.8 and 6.9 tend to support this observation. The sequential lines in figure 6.9 indicate that there are more cooperators then defectors throughout the simulation run, and, after 500 iterations, the number of cooperators in the environment remains relatively stable.

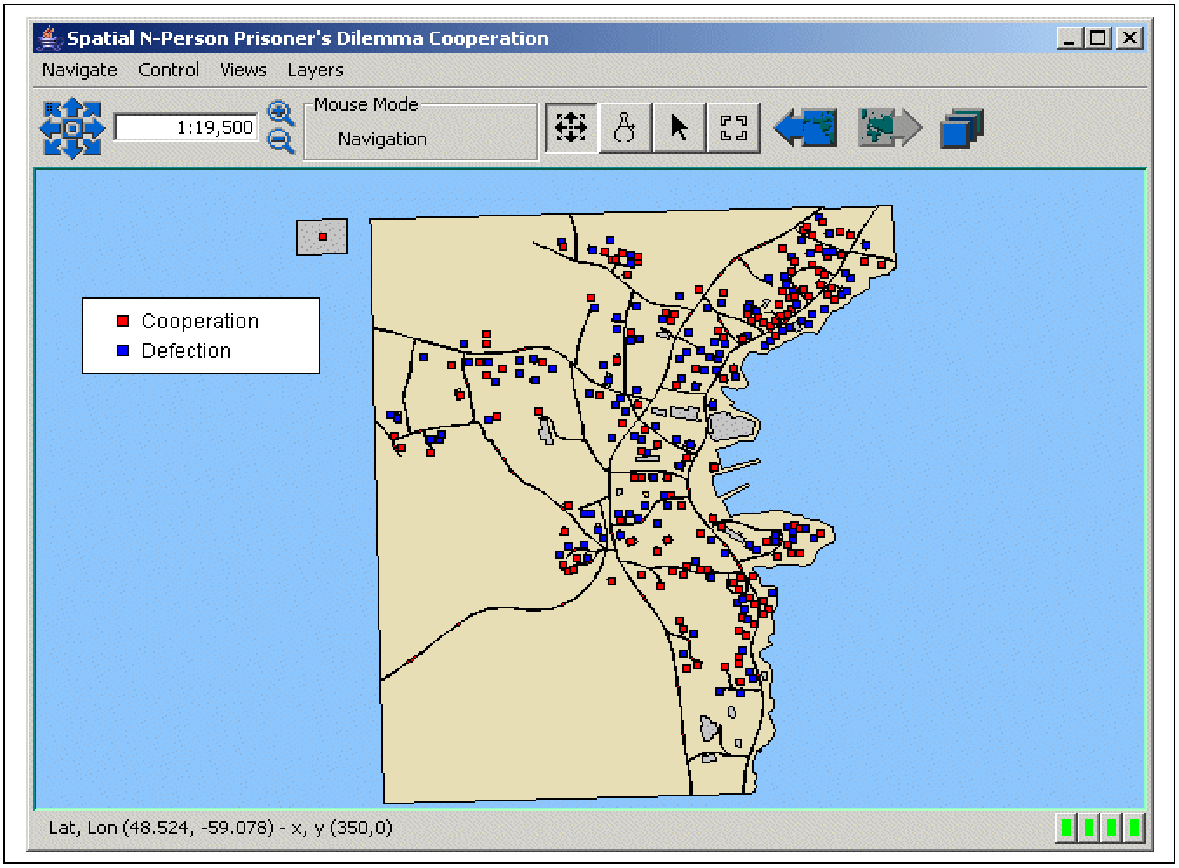

Figure 6.6: Map of Cooperation Pattern for 20% Cooperators and Mobile Citizen Agents

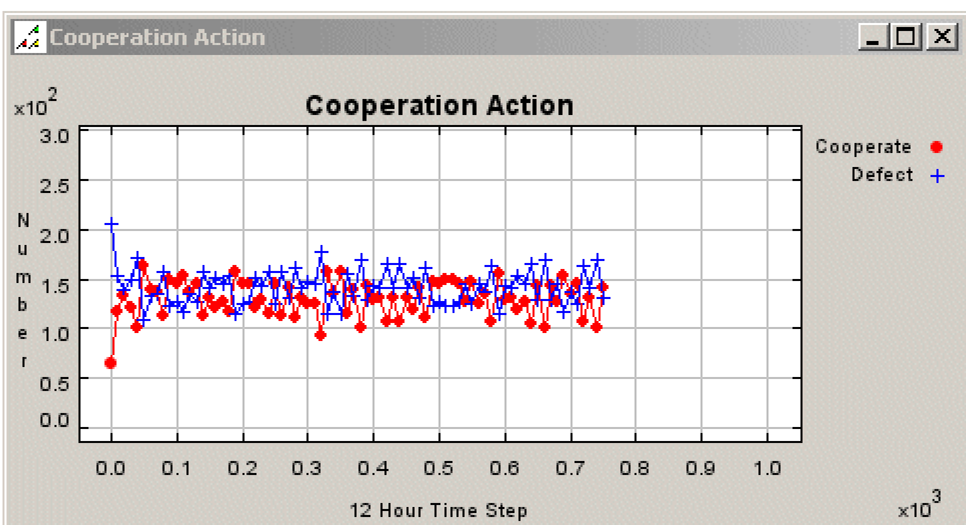

Figure 6.7: Graph of Cooperation Pattern for 20% Cooperators and Mobile Citizen Agents

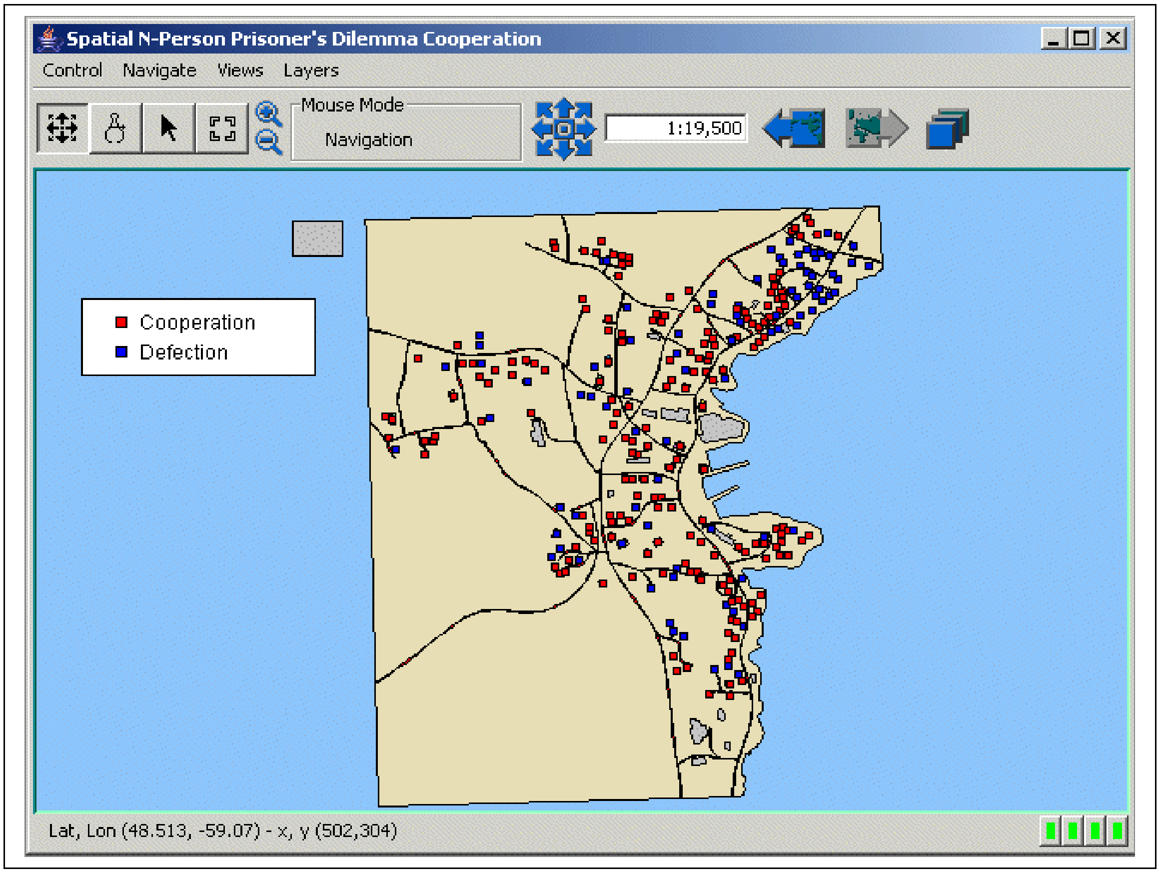

Figure 6.8: Map of Cooperation Pattern for 20% Cooperators and Fixed Citizen Agents

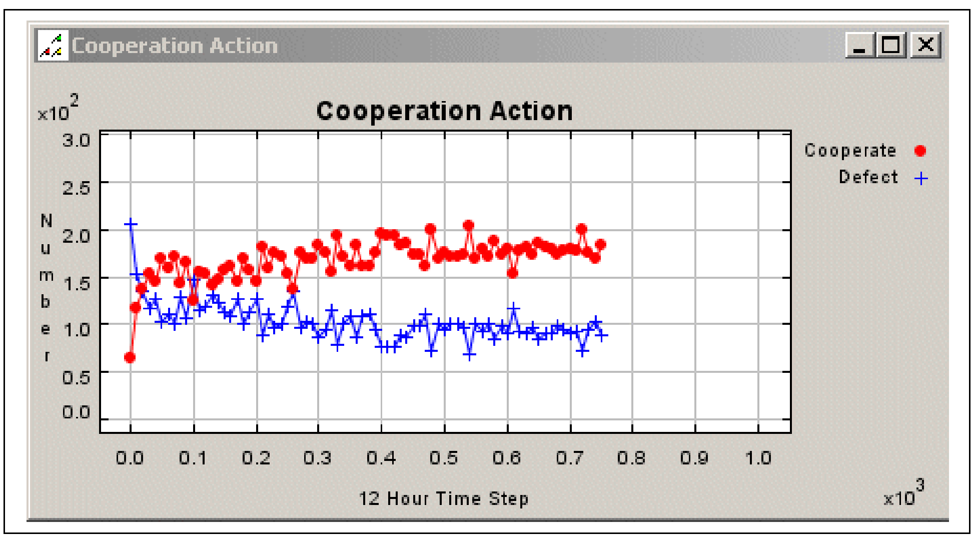

Figure 6.9: Graph of Cooperation Pattern for 20% Cooperators and Fixed Citizen Agents

More importantly, large discernible clusters of C and D are situated throughout the map in figure 6.8, especially the northeast and central sections. The reason for the difference in the emergence and maintenance of cooperation among the purposely fixed and mobile citizens is context preservation in the modeling environment. The fixed citizens are homophily agents that interact with the same neighbours at each time step, which increases their learning rates and probabilities of neighbours at each time step, which increases their learning rates and probabilities of choosing the action of the majority of their social grouping. Conversely, mobile agents experience fluctuations in learning rate and the probability of cooperation as their neighbourhoods change during their daily activities, and this can result in frequent changes in cooperation action.

Similar results were derived for the fixed and mobile agents for the simulations with initialized 80% cooperators. Figure 6.11 shows that the number of agents that choose C and D tend to oscillate, but the overall counts are generally equal during the experiment runs. The spatial patterns changed constantly as a consequence of the transition rules even though the fraction of cooperators remained constant. Small clusters of cooperation and defection are visible on figure 6.10, but it was found that these groupings are highly susceptible to change. An important factor to remember is that these simulation runs contain mobile agents together with fixed workers, such as the people not in the labour force and the unemployed. The small clusters of C and D that emerge are situated around the residences of these fixed

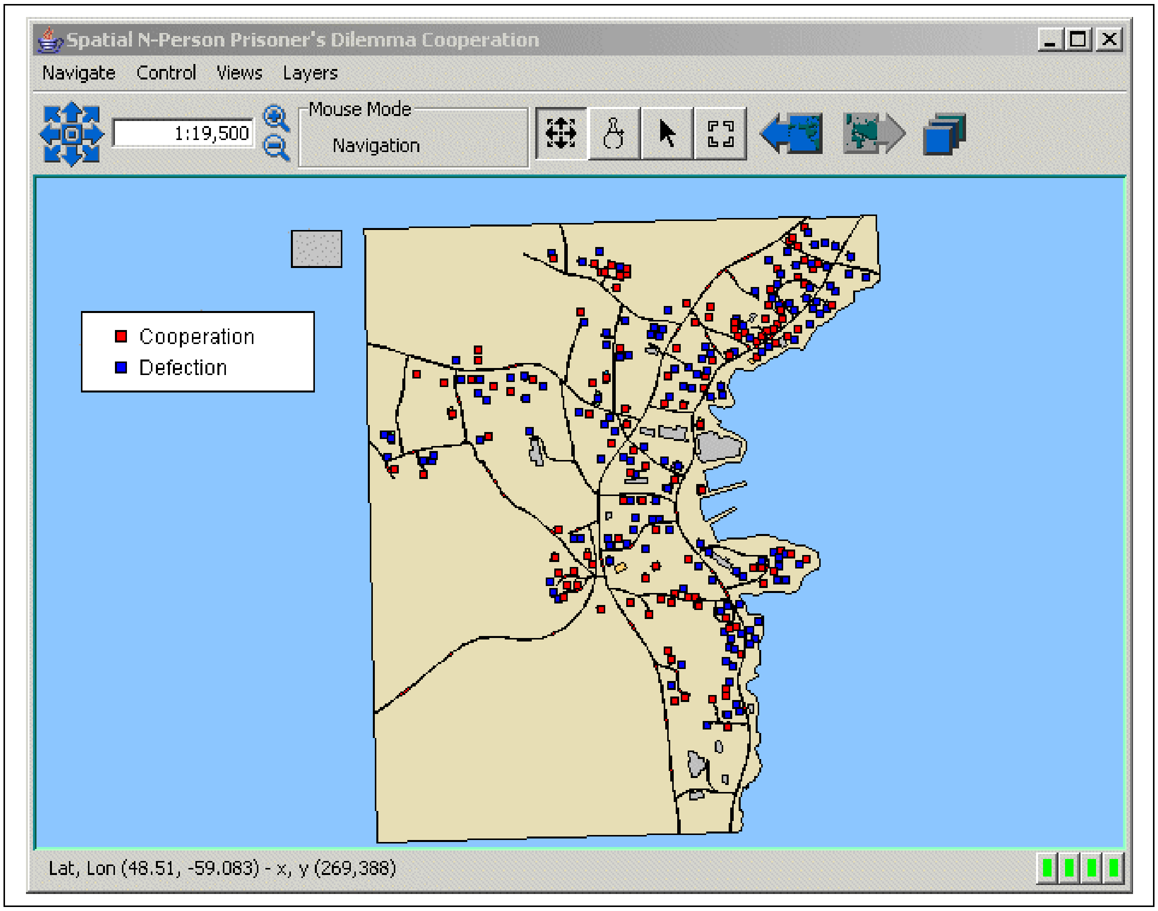

Figure 6.10: Map of Cooperation Pattern for 80% Cooperators and Mobile Citizen Agents

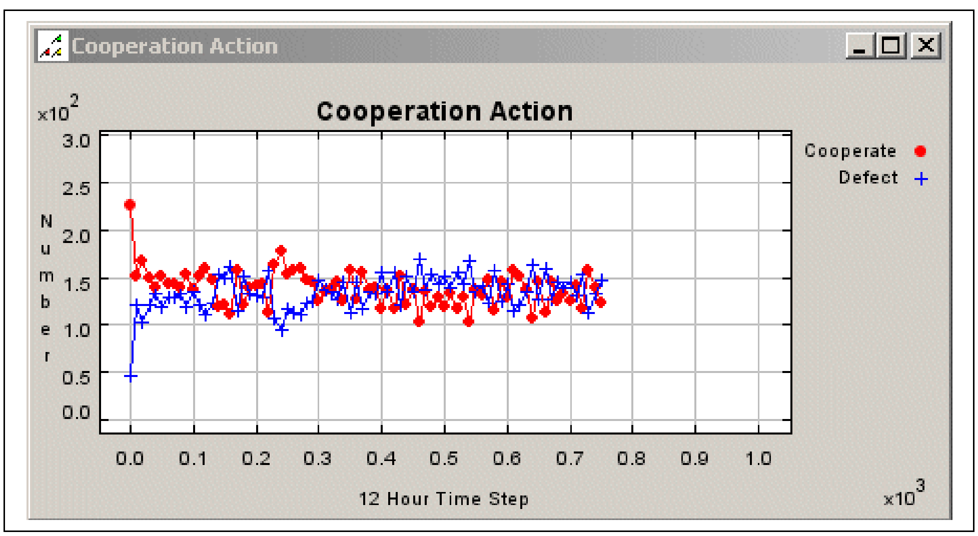

Figure 6.11: Graph of Cooperation Pattern for 80% Cooperators and Mobile Citizen Agents

agents, which further substantiates the importance of context preservation in spatial NPPD modeling. The map and graphing results (figure 6.12 and 6.13) for the fixed citizen agents show that there are more cooperators than defectors during the run and that this situation begins early in the simulation. The sequential linear graphs of the cooperators and defectors are generally constant with periodic minor readjustments at specific time steps. Similarly, large clusters of C and D are evident on the maps. The map in figure 6.12 has visible groupings of C and D in the northeast section and center of the community. This is again due to context preservation, but equally important is the proximity of the agents. An agent that has many citizens within its neighbourhood will have multiple interactions with them during its own NPPD and the others' game play. In other words, the same agents can be grouped many times if they live close to each other, and could start to adopt similar actions over time.

Another interesting observation is the effect the fourth condition of NPPD has on the percentages of C and D, regardless of the initialized cooperation ratio value. Since it's better for society when agents cooperate, a set of transition rules in the model trigger the conversion of D agents to C agents whenever the condition for the 4^{th} condition is violated. Referring to figure 6.13, the simulation starts with 80% defectors, but the system readjusts itself and decreases the number of defectors to approximately 50% at the initial time steps. Although simplistic, this operation is based on the sociological premise that the functioning of a community is hindered or disabled when populated with self-interested individuals. Cooperation is a necessary requirement for social cohesion in a socio-geographic environment.

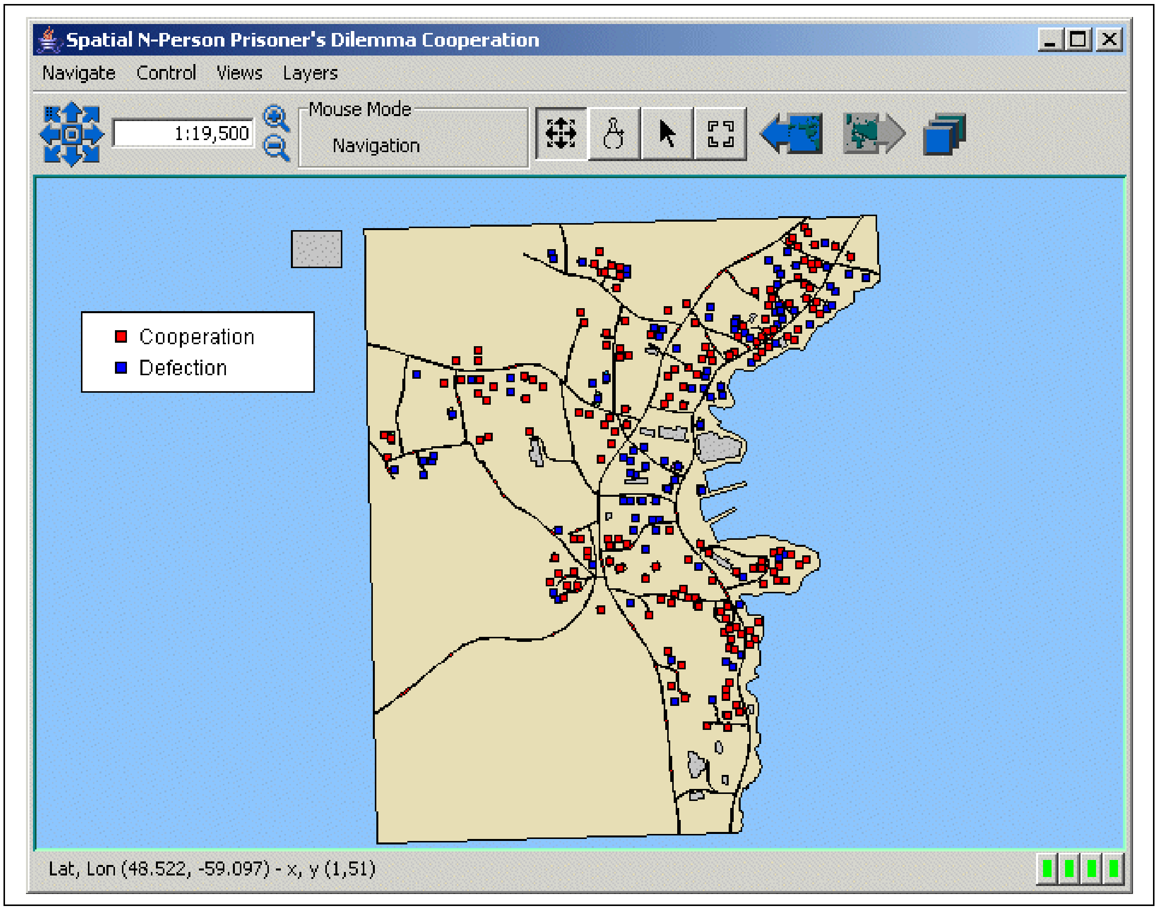

Figure 6.12: Map of Cooperation Pattern for 80% Cooperators and Fixed Citizen Agents

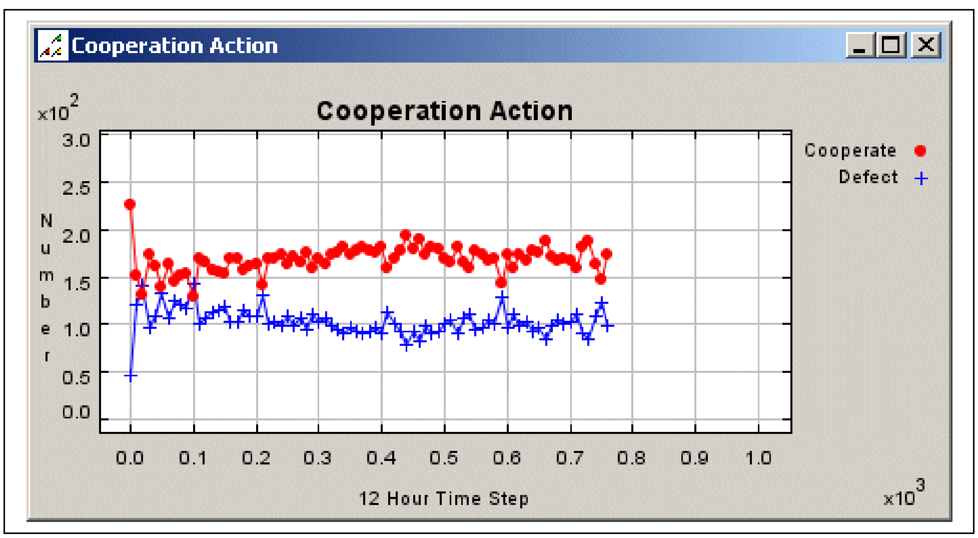

Figure 6.13: Graph of Cooperation Pattern for 80% Cooperators and Fixed Citizen Agents

A spatial agent-based model of NPPD in an analyzed community will contain mobile agents so the better cooperation results for the fixed citizen agent simulations in the examples above is an issue. However, a potential solution is to consider the entire social environment as an additional global neighbourhood so that its immediate neighbours as well as all other agents influence an agent during interactions. From the 4th condition of NPPD, it is logical to consider the complete system as an important neighbourhood in the emergence of cooperation within a realistic socio-geographic community as small as the study area. Therefore, the simulation of cooperation in a model of mobile agents may require transition rules that consider both local and community level processes to model cooperation action dynamics.

6.12 Conclusion

The purpose of this paper is to present a spatial agent-based approach for modeling the processes of communication and cooperation within a socio-geographic community. As a generic modeling-centric system with a tight coupling of REPAST and a vector GIS, the model is designed to simulate the mobility and daily interactions of citizen agents in an analyzed spatial environment. The postulate of the system is that competition and cooperation will emerge from the behaviors of the citizens as they engage in N-Person prisoner's dilemma play. These citizen agents are set as stochastic learning automata that take actions according to probabilities updated on the basis of the reward/penalty received for previous actions, their neighbours' actions, and their Pavlovian personalities.

The value of the model for simulating cooperation in a social-geographic environment was evaluated from the results of two sets of experimental runs. It was determined that the initial percentage of cooperators in a simulation had little bearing on the emergence of cooperation, but the mobility of the citizen automata was the central factor. The preservation of neighbourhood context in fixed citizen agent environments produced larger clusters of cooperators and defectors than the mobile agent environments. As the fixed citizen agents continuously interact with the same neighbours, they become homophily automata with increasing learning rates and probabilities of copying the action of the majority of their social grouping. Conversely, the environments of mobile citizen agents produced small clusters of C and D, but they were susceptible to variations in size and location as the agent neighbourhoods changed. Even though the proportion of cooperators remained constant, the spatial patterns changed repeatedly as a consequence of the movement and action updating rules.

The work presented in this paper is a very simplistic model of cooperation-agent interaction situations and should not be considered a complete analysis of the processes within a socio-geographic community. Future revisions of the model are necessary for it to be applicable to more realistic problems of human interactions in analyzed environments.

The first step towards expanding the model is to investigate the performance of other learning rules, payoff functions, and updating schemes. This version of the model is developed as a linear reward/penalty probabilistic learning automaton system, but the results for the mobile agents are discouraging. It is possible that the learning rules and updating scheme are inappropriate for nonfixed spatial agents and may have to be reconsidered.

Secondly, the classical definition of N-Person prisoner's dilemma is an essentially unrealistic analogy for cooperation, because it only allows a boolean assignment to two cooperation classes. In reality, cooperation should be measured on a continuous state space that varies at each time step according to the attitudes of the agents. Research in this regard has been undertaken by Killingback and Doebeli (2002), who discuss a continuous iterated prisoner's dilemma model of cooperation from reciprocal altruism. A further expansion to the model is to develop a methodology of assigning fuzzy memberships to an agent for both cooperation and defection. Using a set of fuzzy membership functions similar to figure 6.14, each agent is assigned a degree of membership in both classes to produce a continuum of cooperation in the modeling environment. See Power et al. (2001) for a detailed explanation of fuzzy set theory. The advantage of utilizing fuzzy logic in the design of the transition rules and updating schemes is that possibility theory permits memberships values that do not have to sum to 1 (a condition of probability theory). This flexibility could be implemented to account for noise and random errors known to exist in implementing a choice during real-world interactions.

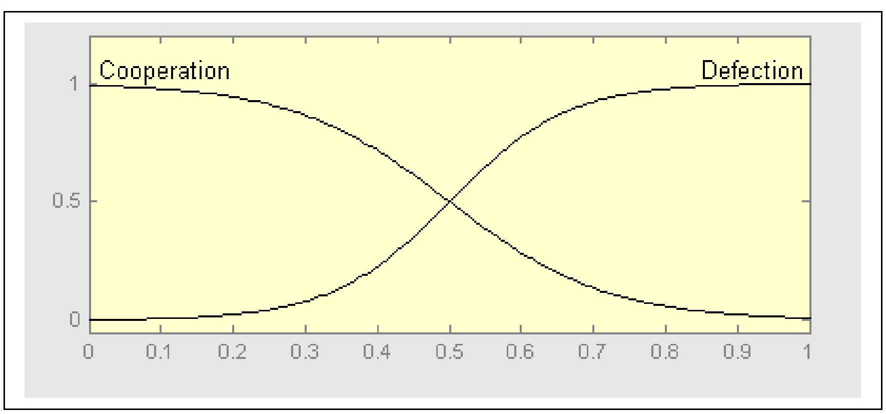

Figure 6.14: Fuzzy Membership Functions of Cooperation and Defection

As a further model revision, a fuzzy inference system can provide a flexible base for developing a modeling component that permits agents to have multiple personality types. Through the combination of fuzzy membership functions for a number of personality types and a compositional rule of inference, a fuzzy transitional rulebase will assign varying degrees of personalities to an agent. The overall personality of an agent then becomes a combination of the degrees of membership in the personality strategies, with the membership values varying at each social dilemma game play. Agents with mixed personalities and interaction strategies are intuitively appealing for a spatial agent-based model of cooperation in a socio-geographic environment.

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7.0 Paper 2: Affective Cooperation in the N-Person Prisoner's Dilemma. A Spatial Agent-Based Modeling Perspective

Abstract

The purpose of this paper is to present a spatial agent-based model of affective N-Person's Prisoner's Dilemma to study the cooperation dynamics in a socio-geographic community. The benefit of the affective model over the traditional approach is the ability to assign psychological personalities to the agents which enable them to exhibit believable behaviors. The proposed integrated model has a spatial module to simulate the mobility events and neighbourhood composition of agents, a Personality-Mood-Emotion psychological component to model affective states, and a N-Person's Prisoner's Dilemma social interaction mechanism to simulate communal behaviors and emergent cooperation. The layered model of affect is presented as the mapping of the five factor OCEAN model of personality, Mehrabian Pleasure-Arousal-Dominance Mood spacing, and the Ortony, Clore, Collins model of emotions. This hierarchical structure of affect is developed to first calculate the individual intensities of the emotions from the action choices of neighbours and the outcome of social exchanges. An additional readjustment of the intensities of the emotions happens during the computation of a comprehensive affective state as the influence of mood state and personality are considered.

The capabilities of the system are demonstrated with benchmark simulation results. Clustering of cooperators tend to emerge at locations where the agents remain in a homophily neighbourhoods for multiple time steps. This highlights the importance of context preservation and neighbourhood strength on the emergence of cooperation in the environment.

7.1 Introduction:

Since the early 1990s, the N-Person Prisoner's Dilemma (NPPD) has been a research topic of spatial and social modelers who are interested in the emergence of cooperation in social groupings. Akimov and Soutchanski (1994) developed a spatial NPPD game to relate how cooperation in social networks depends on the behavioral patterns of simple automata within a cellular automaton. Szilagyi (2003) presented a model of NPPD based on the interactions of irrational agents in a social unit and revealed how the chaos like actions of the agents was an important condition for decentralized group cooperation. Power (2009) presented a spatial agent-based model of NPPD that simulated the emergence of cooperation from the behaviors of mobile citizen agents in a socio-geographic community. However, the basic NPPD designates the interaction strategies of the agents as proxies for human personalities, but they have little relevance to a psychological personality. A formalization of social interactions that are independent of the emotional states of agents restricts their autonomy and generalizes the complexity of individual decision-making during simulation episodes.

The purpose of this paper is to present a spatial agent-based model of affective N-Person's Prisoner's Dilemma to study the cooperation dynamics of agents in a socio-geographic environment. The integrated model consists of a spatial component to simulate the automata mobility behaviors and neighbourhood structures, a Personality-Mood-Emotion psychological mechanism to handle the affective states of the agents, and a NPPD component to simulate social interactions. The discussion about the design of the model begins with a brief overview of the theory of the

NPPD. The following section explains the layered framework of the Personality-Mood-Emotions model comprised of the five factor or OCEAN model of psychological personality, Mehrabian Pleasure-Arousal-Dominance (PAD) Mood spacing, and the Ortony, Collins, and Clore (OCC) model of emotions. Attention will be paid to procedures of mapping and linking each component into a layered affective model. Next, a methodology section presents a rule based inference system that links emotional affect to NPPD game play, where the probability of an agent choosing a specific action depends both on the affective states before and after a payoff is received.

The discussion proceeds with model experiments that explore how the mobility dynamics and comprehensive affective state of the agents influence the emergence of cooperation in the environment. A summary of the experiment findings as they relate to emergent cooperation concludes the paper.

7.2 N-Person Prisoner's Dilemma

NPPD models have been referred to as social dilemma games, because they are focused on the simulation of the communal actions and behaviors in social groups (Schelling, 1973). During play, individual players may cooperate with each other for the benefit of their social network, or they may prefer to pursue their selfish interests. In multi-player interactions, cooperation emerges from the consensus behaviors and actions of the social unit even though the preferred course of action for an individual player is still defection.

A typical social dilemma can be considered an n-person game (n > 2), in which each player has the same preferred option that does not change regardless of the actions of the other players. Every player has the same payoff structure and can choose to either cooperate, C, or defect, D. Figure 7.1 is a graphical representation of an example situation that shows the payoff functions for a player that chooses the preferred defection option (P) or the un-preferred cooperation (U) alternative, depending on the number of other players (0 to n) that choose U.

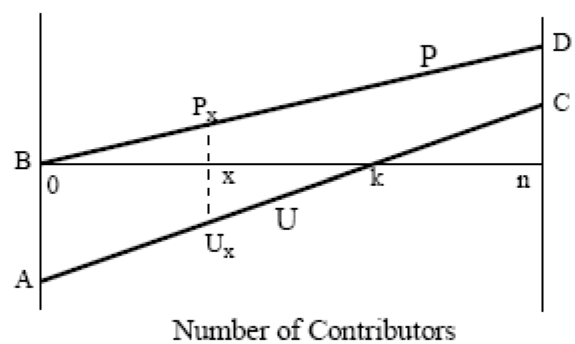

Figure 7.1: N-Person Prisoner's Dilemma Payoff Functions for Preferred Defection and Un-Preferred Cooperation, Relative to the Number of Other Players that Decide to Cooperate:
(from Akimov and Southchanski, 1994)

To illustrate, at x = n/3, a third of the players choose to cooperate and two thirds defect: P_x and U_x are the payoffs to the player that chooses the defection (preferred) or cooperation (un-preferred) alternatives, respectively. The payoff functions are structured so that each player receives a higher payoff for defection than for cooperation. A player's decision to cooperate or defect is therefore dependent on the number of cooperators and defectors in his neighbourhood and the utility of the payoff functions at each time step of the play sequence.

7.3 Personality-Mood-Emotion Model of Affect

An addition to the scope of spatial agent-based research is the capability of automata to show emotions in their behaviors as they perform everyday activities within an environment. Emotions will serve a number of purposes, from increasing the believability of the actions of the agents to motivating agent behaviors in cooperation decisions. Kennedy (2012) presents a set of basic principles to consider in simulating human behaviours with agent-based models. He discusses the real world condition that human decisions are often directed by emotional drivers and the complex behaviours exhibited by individuals are also influenced by the effects of mood. The development of a model with a cognitive architecture requires mechanisms that more accurately represent the human mind both in perception and affective response to social interactions. Kasap *et al.* (2009) demonstrate that emotions have proven effects on agents' cognitive processes such as action selection, learning, memory, motivation, and planning.

Gebhard (2005) presents an implementation of a psychological mechanism in an agent-based model that simulates cognitive processes as a layered model of affect. It is designed to simulate the three interacting kinds of affect that occur in human decision making:

1. Emotions – represent short-term affect and are usually associated with a specific event, object, or action. Emotions tend to dissipate when the agent changes focus.

2. Moods – reflect medium-term affect and are not associated with a specific event, object, or action. Moods have a temporal effect on cognitive functions that decays with each successive interaction sequence.

3. Personality – represents long-term affect and is defined by individual differences in mental characteristics. Personality is an atemporal state that generally remains constant throughout a life span of an agent.

The Personality-Mood-Emotion component of this study utilizes the same layered approach, but relates the emotional state of the agents to the anticipated and resultant outcomes of NPPD episodes. The specification of the affective module follows the standard approach employed by numerous researchers (Egges *et al*., 2003; Ghasem-Aghaee and Oren, 2003; Gebhard and Kipp, 2006; Mustafa *et al*., 2008; Kasap *et al.,* 2009) of integrating the five factor model of personality, Mehrabian PAD spacing mood determination, and the OCC model of emotions.

7.3.1 The Big Five Factor Model of Personality

The five factor model is founded on the principle that the many ways in which people differ in their emotional and attitudinal styles can be summarized with the five basic traits of Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism (McCrae and Costa 1987; Goldberg 1992):

- Openness (O). Open people are imaginative, intelligent, and creative. They like to experience new things.
- Conscientiousness (C). Conscientious people are responsible, reliable, and tidy. They think about all their behaviors' outputs before acting and take responsibility for their actions.
- Extroversion (E). Extroverts are outgoing, sociable, and assertive. They're energetic in achieving their goals.
- Agreeableness (A). Agreeable people are trustworthy, kind, and cooperative. They consider other people's goals and are ready to surrender their own goals.
- Neuroticism (N). Neurotic people are anxious, nervous, and prone to depression. They lack emotional stability.

From a modeling perspective, a unique personality can be assigned to an individual by varying the values of each OCEAN factor within the range of -1 to 1. The appeal of the five factor model is that the variety of individual personalities that can be generated during model initialization is nearly boundless. Also, the five traits are intuitively sensible and computationally simple, and provide a basis for relating personality to other psychological phenomena. Specifically, the framework of OCEAN can be mapped to an individual's mood with Mehrabian PAD mood spacing.

7.3.2 Mehrabian Pleasure-Arousal-Dominance Mood Spacing

Mehrabian (1995) conducted a study to determine how his PAD temperament model could be theoretically linked to the five-factor model. He demonstrated how the commonality of descriptive emotional adjectives and measurement scales between the two approaches relate the three mood traits of Pleasure, Arousal, and Dominance to the five OCEAN components. This produces an alternative personality framework that includes mood types into the estimation of the emotional states of individuals.

Mood is a medium term affect that decays with time so it can be computed as the average of a person's emotional states for a sequence of events and actions. In the PAD model, Pleasure, Arousal, and Dominance are orthogonal traits that form a mood space, which is implemented as a three dimensional Cartesian coordinate system with an axis ranging from -1.0 to 1.0 for each trait. The strength of each trait is the distance from the origin measures along the given axis, and the three distances setting the Cartesian positioning of the mood space. Mood is described with the following classification of each of the three mood space axis: +P and –P for the emotional state's positivity or negativity, +A and –A for mental arousal and alertness or mental inattentiveness, and +D and –D for feeling of social control and behavioral submissiveness. Table 7.1 lists all octants of the PAD mood space.

Table 7.1: Mehrabian Mood Octants and Mood Types

Trait Combination (Octant)	Mood Type
+P +A +D	Exuberant
-P -A -D	Bored
+P +A -D	Dependent
-P -A +D	Disdainful
+P -A +D	Relaxed
-P +A -D	Anxious
+P -A -D	Docile
-P +A +D	Hostile

The first factor in implementing mood is initializing each trait to position personality within a PAD spacing. Mehrabian (1996) devised a set of equations to translate the 5D personality vector ***P*** into a default PAD mood spacing. The base mood of an individual is:

$$\boldsymbol{P} = (O,C,E,A,N),\ O,C,E,A,N \in [-1,1]$$

$$Mood_{base} = (P_1, A_1, D_1)\ ,\ P_1, A_1, D_1 \in [-1,1]$$

$$P_1 = 0.21E + 0.59A + 0.19N \tag{7.1}$$
$$A_1 = 0.15O + 0.30A - 0.57N \tag{7.2}$$
$$D_1 = 0.25O + 0.17C + 0.60E - 0.32A \tag{7.3}$$

The second factor is the handling of individual mood changes. Russell and Mehrabian (1977) provide the methodology for simulating mood change from the association of PAD mood space to OCC emotions. Table 7.2 shows a portion of their suggested mapping for several basic emotions to specific PAD spacings. Each emotion type is succinctly described in terms of a set of values on the PAD axes that associates emotion to a PAD octant and mood type. For instance, joy is linked to an exuberant mood type and +P+A+D mood octant.

Table 7.2: Mapping from OCC Emotions to PAD Mood Space

Emotion	Pleasure	Arousal	Dominance	Mood Type	Mood Class
Joy	0.40	0.20	0.10	+P+A+D Exuberant	Positive
Distress	-0.40	-0.20	-0.50	-P-A-D Bored	Negative
Hope	0.20	0.20	-0.10	+P+A-D Dependent	Positive
Fear	-0.64	0.60	-0.43	-P+A-D Anxious	Negative

Mehrabian (1995) updated mood with a function that calculates change in the emotional state of an individual. For example, when a person experiences the emotion joy, the mood spacing will be adjusted so that the Pleasure, Arousal, and Dominance values are all positive, which puts him in an exuberant mood.

7.3.3 Appraisal Theory and Ortony, Clore, and Collins Model of Affective Emotions

Several authors (Ortony *et al.*, 1988; Bartneck, 2002; Kasap *et al.,* 2009) present the OCC model as the standard approach for emotion synthesis utilizing cognitive appraisal theory. Cognitive appraisal theory asserts that emotions are elicited and differentiated on the basis of a person's subjective appraisal of the significance of a solution, object, or event according to a set of criteria conditions (Scherer, 1999). The advantage of appraisal theory for affective models is that the evaluation of emotion-eliciting objects or events is highly subjective and depends on the individual's perceived goals, values and coping potential (Smith and Pope, 1992). This ability of appraisal theory to explain why seemingly similar events can trigger highly disparate emotions in different people is central to the appeal of OCC model.

Emotions are seen as the reactions to three types of appraisals: the appraisal of events with respect to agent goals, the appraisal of agents with respect to the praiseworthiness of their actions compared to a set of standard behaviours, and appraisal of objects from the appeal as determined by agent attitudes (Ortony, 2003). Figure 7.2 gives an overview of the original OCC hierarchy that specifies twenty-two emotion categories and two cognitive states based on valenced reactions to the consequences of events, actions of agents, and aspects of objects.

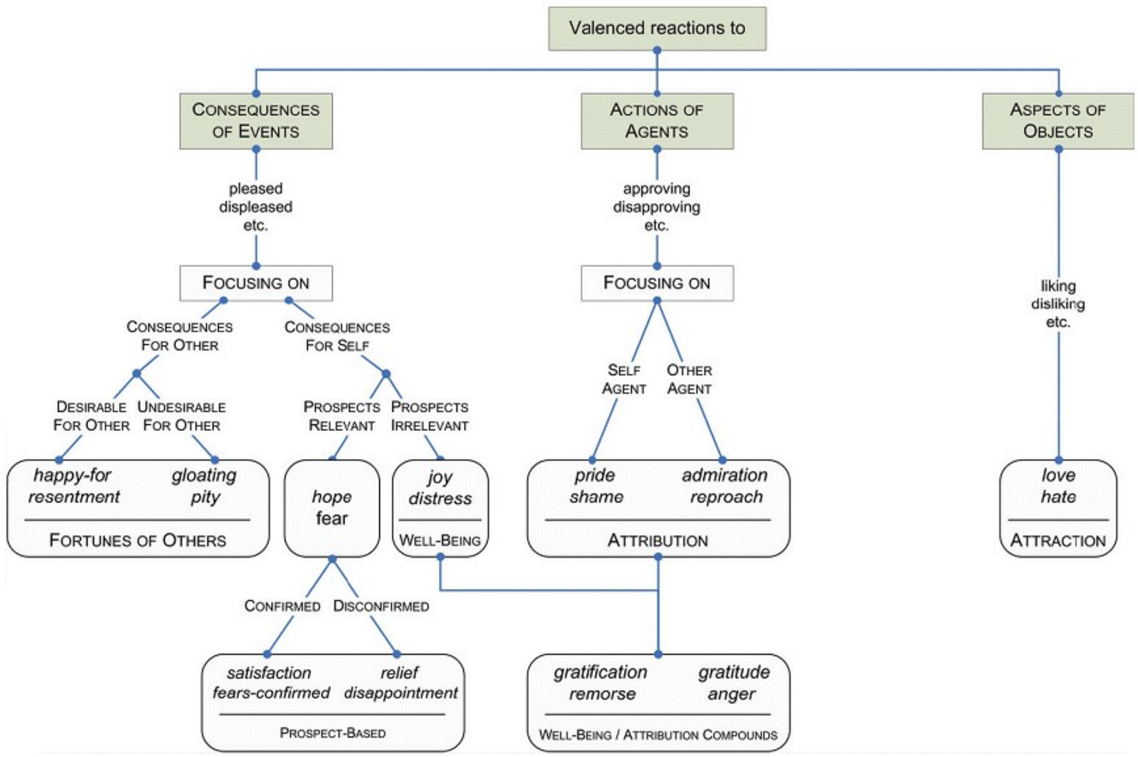

Figure 7.2: The Original OCC Model (Source: Kessler *et al.,* 2008)

The event-based emotions in the left branch arise when an agent determines the consequences of an event as being either desirable or undesirable. Desirability is the key factor that sets the intensity of all event-based emotions and is the main criterion for evaluation. Four classes constitute the event-based emotions. The first class is the fortunes-of-others, which includes the emotions happy-for, resentment, gloating, and pity. The intensity of these emotions depends on processing events that have consequences for other agents. The second and third classes are contingent on processing events that have consequences for self. Appraising an event by evaluating its prospects is fundamental to the second class and depends on hoping or fearing that something will or will not occur. The third class is the well-being emotions of joy and distress that are the direct result of whether an agent is directly pleased or displeased with the results of an event. The last class is confirmation, with satisfaction, disappointment, relief, and fears-confirmed.

The middle branch contains the general class of emotions associated with approving and disapproving, and has a single class called attribution that contains the emotions pride, shame, reproach, and admiration. These are caused by reactions to the actions of agents that are evaluated as being either praiseworthy or blameworthy (Ortony *et al.,* 1988). When the actions of other agents are appraised, the emotions triggered are admiration or reproach. An additional class of attribution emotions is referred to as the compound classes. The compound emotions are derived from the conjunction of the eliciting conditions of a well-being emotion with an attribution emotion, and, focus on both the outcome of the event and the desirability of the result. The four compound emotions are gratification, gratitude, remorse, and anger.

The right branch comprises the affective emotions from the reactions of liking and disliking. These are the attraction emotions, which are activated by reactions to objects or aspects of objects relative to appealingness. This branch of emotions has a single class of attraction, which includes love and hate.

The theory of the NPPD is such that the emotions experienced by the agents can be valenced reactions to the consequences of social exchanges and the actions of agents towards cooperation or defection. It was decided that the OCC structure for this model be limited to a set of basic emotions that can be characterized by a set of decision rules relevant to the NPPD procedure. Specifically, the prospect-based emotions of hope and fear and the well-being emotions of joy and distress can be measured from the outcomes of NPPD events and the memories of past social interactions. The attribution emotions of admiration and reproach will indicate the positive or negative affects of the level of cooperation in each interaction neighbourhood. Anger is also included to investigate how the combined intensities of primary emotions can produce a compound affective state.

7.4 Methodology

The main consideration in the development of a spatial agent-based model of affective N-Person Prisoner's Dilemma is that the actions and behaviors of agents have to better approximate human decision-making during social interactions. The agents have to be represented as autonomous entities that make decisions according to their individual affective states and social position in the modeling environment.

The architecture of the agent-based model in figure 7.3 shows the functional integration of pre-simulation initialization methods with the simulation components. A synthesized population of agents is assigned default personality and mood space states by the initialization methods. During simulation, spatial, psychological, and social processes are modeled to simulate the emergence of cooperation among individuals in the environment.

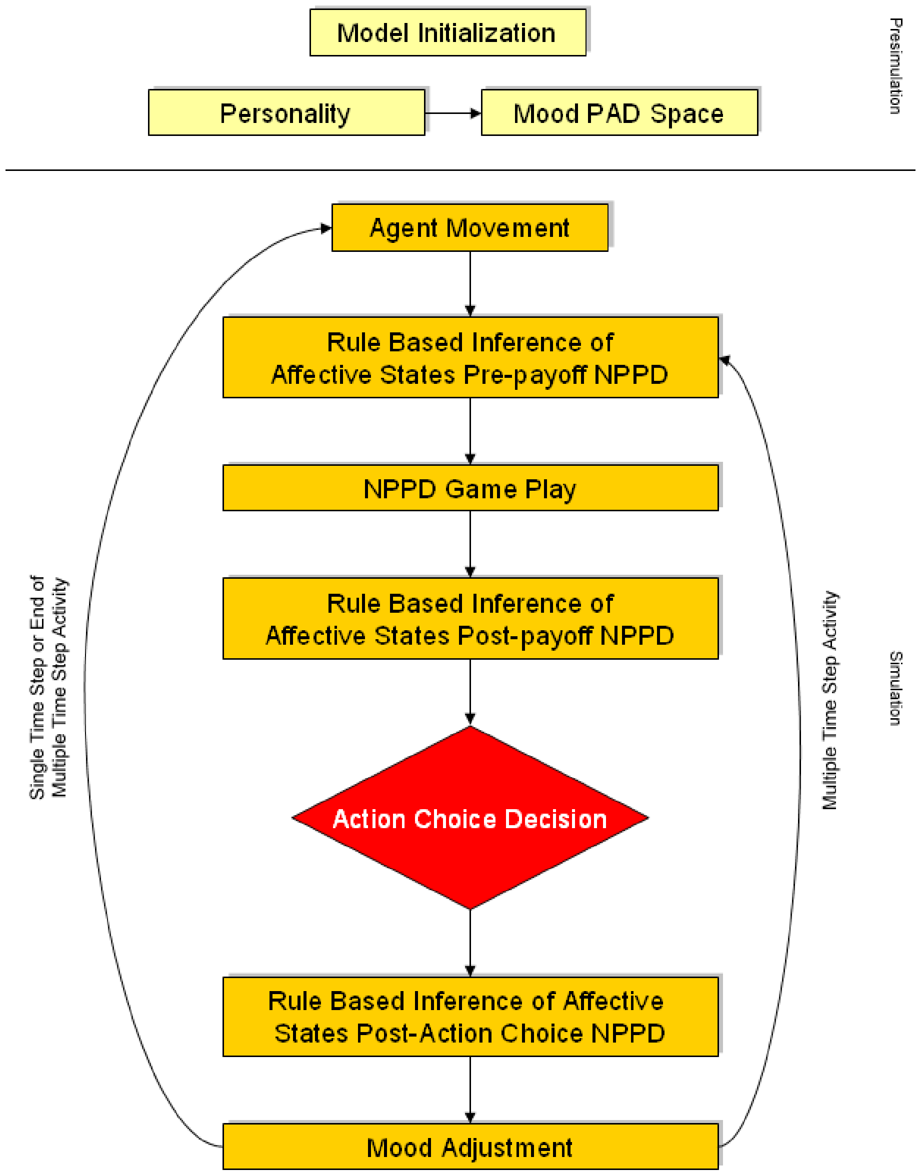

Figure 7.3: Model Architecture

7.4.1 Model Initialization

The first stage in the model initialization is to assign the agents a default personality as a five dimension OCEAN vector. Each trait is given a randomly generated initial value between –1 and 1, but the assignment can be restrained to several default personality types as listed in table 7.3.

The second stage in the model initialization is the setting of an initial mood state. Once personality has been set, a default mood state for each agent can be calculated with the OCEAN Mapping to Mehrabian PAD spacing equations previously discussed.

Table 7.3: OCEAN Schemas for Extreme Personality Type

Personality Type	**O**	**C**	**E**	**A**	**N**
Open Extrovert	High	Neutral	High	High	Low
Neurotic Introvert	Low	Neutral	Very Low	Low	Very High
* Neutral (≈ 0), Very Low (≈ -1), Very High (≈ 1)					

7.4.2 Simulation and State Transition Rules

Figure 7.3 reveals the sequence of simulation components in the model, each containing state transition rules for modeling the mobility, psychological, and social processes of agents engaging in activities in a geographic environment. Simulation begins with a spatial component to model agent movements and compute the depth of neighbourhood configuration after each movement.

7.4.2.1 Agent Movement

Agent movements are simulated as discrete choice events, in which a scheduling mechanism directs the sequencing of agents' mobility behaviors. This requires movement rules that manage both the single time step and multiple time step activities of the citizen agents. Both types of mobility are scheduled in an asynchronous manner, where the agents move from origin to destination locations at a specified time step. The location of an agent at each time step depends on its randomly selected activity, either a church, recreation, retail, service, friendship gathering, school, or work event. Movement is therefore a two-step process of first choosing an activity for the time step and secondly selecting the location of where the agent will carry out the activity. When an agent moves to a location, he remains at that site for the associated time period.

7.4.2.2 Interaction Neighbourhoods

The depth of an interaction neighbourhood defines the extents of the spatial association of a social grouping within the environment. An important factor of representing mobile automata in a geographic environment is that movement can produce a change in the locational topology of the agents. The rule set for neighbourhood delineation is based on the proximity of agents on a geometric network, where agents within a specified distance of each other are considered neighbours. At each time step, the topology and automata composition of the neighbourhood for each citizen agent is estimated with a buffer drawn around the location of each agent, and all individuals that fall within the buffered area are classified as neighbors.

7.4.3 The Layered Model of Affect of NPPD Game Play

An affective NPPD network consisting of event-based and attribute emotions, where actions are evaluated with respect to the goal of receiving a reward payoff and the emergence of group cooperation. Figure 7.4 displays the OCC hierarchy of the emotional model of affect for NPPD game play.

The event-based emotions arise when an agent determines the consequences of a NPPD event as being either desirable or undesirable, and desirability refers to the degree of wanting the social interaction event to produce a positive payoff and the emotional affect of this resultant reward or penalty.

7.4.3.1 Rule Based Inference of Affective States Pre-NPPD

The Personality-Mood-Emotions component is structured as a conditional rule-based system that simulates the affective states of agents from their mobility activities, neighbourhood configurations, and the action choices from the outcomes of

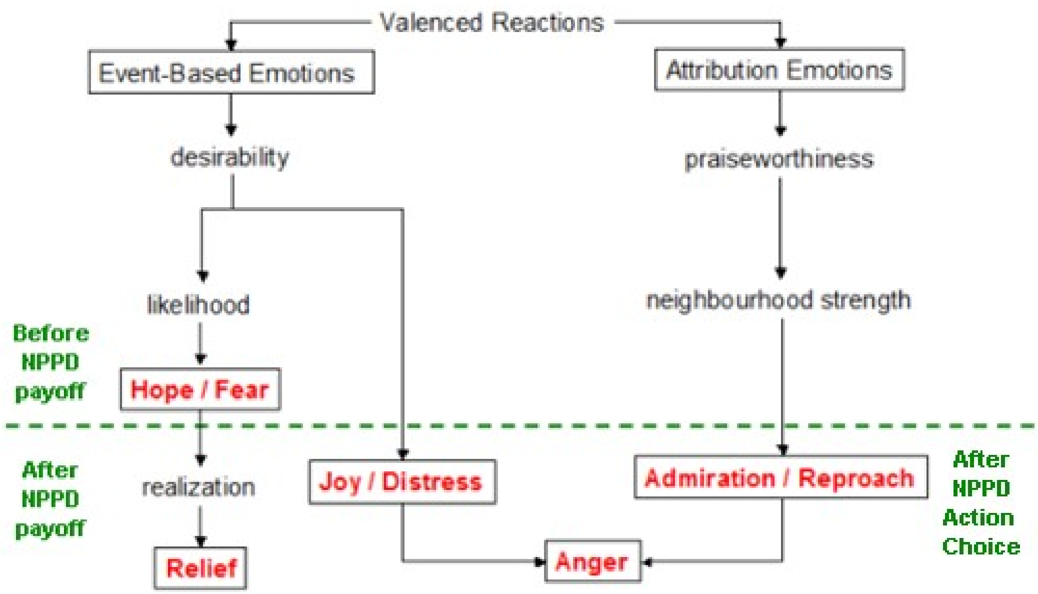

Figure 7.4: OCC Emotions for NPPD Game Play

social interaction events. The rule-based model consists of pre-payoff, post-payoff, and post action choice NPPD If-Then conditional statements to synthesize the intensities of the emotions felt by each agent. The rules for each of the event based emotions and attribution emotions in the appraisal system are detailed in appendix 1.

The prospect based emotions of hope and fear depend on the degree to which an NPPD event is pleasing or displeasing to an agent, but also must be appraised according to the likelihood of getting a reward from an upcoming social interaction. For these anticipative affects, the likelihood of an event must evaluate desirability, because it makes little sense to desire an outcome from an event that is unlikely to happen. Thus, hope relates to the prospect and anticipation of getting a positive payoff. Fear, on the other hand, is based on the prospect and expectation of receiving a negative payoff. The If parts of the rules for hope test desirability and the likelihood of receiving a positive payoff, while the If parts of the rules for fear only test likelihood of receiving a negative payoff. The Then action for both sets of rules determines the potential for generating the emotion and directly sets its intensity.

The likelihood of activating hope and fear is reliant on the cooperation composition of the neighbourhood, but as pre-NPPD emotions, this has to be derived from the memories of each agent about the past cooperation decisions of their neighbours. An agent would only know the current action choice of a neighbour if both had participated in the same NPPD event at time *t*. So, there will be instances where the agent is unaware of some or all of their neighbours' action choices at time *t*, especially for the single time step mobility activities. This issue is addressed in two ways. First, each agent is assigned an arraylist state attribute that stores the last experienced action choice of past neighbours. After a neighbourhood composition of an agent is identified, the agent refers to this arraylist to set each associated action choice of its neighbours as their cooperative state at time *t*. Secondly, an agent that has no record of a neighbour's last action choice randomly sets him as a cooperator or defector.

As the total number of known cooperators within a neighbourhood increases, the higher the likelihood that an agent will experience hope and fear. The desirability of hope then is a function of the likelihood of receiving a positive payoff and the payoff history of the agent. An agent will desire a positive payoff more if he has received negative payoffs over a series of time steps. For fear however, desirability is zero, because no agent wants to receive a negative payoff.

The activation of a prospect emotion requires the determination of its Personality-Mood-Emotions intensity *(I_{PME}),* and this is conditioned on the emotional intensity I_E computed from likelihood and desirability of a potential payoff, the intensity of temporal mood PAD state (I_M), and, sometimes, the degree of neuroticism of the agent. The level of I_E for hope is high whenever the likelihood and desirability are both high, because the agent anticipates that the positive payoff that he greatly wants will be obtained in the upcoming NPPD event. As likelihood decreases, the intensity of hope lowers to a point that the effect of desirability is negated. An agent will not desire an event that is unlikely to happen. Fear is initially assigned an I_E setting referring to the likelihood of getting a negative payoff. The higher the likelihood, the more intense the level of fear, and vice versa.

The middle term temporal mood PAD state is an important component for determining the short term intensity of emotions for several reasons. Firstly, it incorporates the influence of the post-payoff and post action choice NPPD emotions into the probability of an agent choosing a specific action during game play. The combined affective intensities of joy, distress, relief, admiration, reproach, and anger from the result of a social exchange at time step *t* are embodied in the mood PAD spacing, which is a contributing factor in setting the overall affective state of an agent at time step $t+1$. Referring to appendix 1, a positive I_M value raises the intensity of hope and decreases the intensity of fear a random amount while the contrary situation occurs for a negative mood state. Secondly, the temporal mood state becomes the default means of setting the I_{PME} whenever the level of I_E is negligible or zero.

In situations where I_E and I_M are both approximating zero, the long term affect of the neuroticism of an agent will influence the computed I_{PME} level. By their propensity to be easily stressed and overreact in social situations (Miller, 1991), extremely neurotic individuals will be less hopeful and more fearful and their corresponding affective intensities will be lessened and strengthened accordingly. The opposite condition applies to individuals with low neuroticism levels.

At the completion of the pre-NPPD affective state evaluation, the comprehensive intensity values I_{Hope} and I_{Fear} values are passed to the social component of the model to begin the affective NPPD game play.

7.4.3.2 Affective N-Person Prisoner's Dilemma

Each agent is a stochastic learning two-step memory entity with a Pavlovian interaction strategy, a randomly assigned initial action choice, OCEAN personality, and default mood PAD spacing. A Pavlovian agent utilizes a coefficient of learning to change the probability of cooperation by an amount proportional to the reward/penalty it receives from the environment

At each time step, an agent is randomly assigned a discrete choice activity, which requires either movement to a randomly chosen activity specific location or staying at the current geographic position. After the mobility events, the model calculates the neighbourhood of each agent and determines the total number of cooperators and defectors in that grouping. The interaction proceeds as the reward/penalty for each agent is computed from a set of payoff functions. Lastly, each agent updates his action choice (C or D) according to a weighted reward/penalty estimation derived from two-step memory payoff values and the influence of its interaction strategy. An affective Pavlovian agent adjusts the probability of cooperation by the emotional intensities of hope, fear, relief, joy, and distress, by an amount proportional to the reward/penalty it received from the environment, and the influence of its coefficient of learning.

The emotional fine-tuning of the probability of cooperation for the agents occurs before the agents choose an action, and this happens both before and after the agents receive a payoff for the NPPD event. Therefore, the probability of cooperation for agent i at time step t, notarized as $p_i(t)$, is reset first according to the agent's intensities of fear and hope, and then by relief, joy, and distress. The initial stage pre-payoff NPPD affective state is computed as:

$$I_{prePayoff} = (I_{Hope} + 0.1) + (I_{Fear} - 0.1) \tag{7.4}$$

As the social interaction begins, the reward or penalty received is computed from a set of functions considering the neighbourhood composition and the action state of the agent. The payoff curves for both the defectors and cooperators are straight lines functions expressed as (Szilagyi, 2003):

$$D = -0.5 + 2x \tag{7.5}$$

$$C = -1 + 2x \tag{7.6},$$

where x represents the ratio of the number of cooperators to the total number of neighbours.

Once the agent has collected a reward or penalty, the post payoff intensities of relief, joy, and distress are computed, and the probability of cooperation adjusted by the confirmation and well being emotional states. Thus, the comprehensive post-payoff affective state is:

$$I_{Postpayoff}=(I_{Relief} + 0.05) + (I_{Joy} + 0.1) + (I_{Distress} - 0.1) \tag{7.7}$$

The emotion adjusted probability of cooperation for agent *i* is then set as

$$p_{ei}(t) = p_i(t) + I_{prePayoff} + I_{postPayoff} \tag{7.8}$$

The emotion adjusted probability of defection is thus derived from :

$$q_{ei}(t) = 1 - p_{ei}(t) \tag{7.9}$$

Next, the action strategies represent the interaction histories of agents as a weighted payoff, an average production function, and a coefficient of learning. Given a citizen agent, the weighted payoff is defined as

$$RPwt = \sum_{i}^{3} W_i Mc_i, \text{ where } \sum_{i}^{3} Wi = 1 \tag{7.10}$$

and Mc_i is the history payoff (i.e. Mc_1 stores the current payoff). Assuming that the effects of memory decrease with time, $W_1 \geq W_2 \geq W_3$.

The updating scheme is a set of functions that assign an action to an agent probabilistically based on his behavior and the behaviors of his neighbours in the social grouping from three-step memory events. At each iteration, agent *i* changes $p_{ei}(t)$ and $q_{ei}(t)$ according to the reward/penalty received from the environment's responses. For instance, if at time *t*, the agent chooses C and the payoff functions reward it, then the probability of choosing C is increased for subsequent time steps. Each agent is also assigned a coefficient of learning α_i, where $0 < \alpha_i < 1$, to adjust the probability according the neighbourhood responses and past cooperation states. α_i increases if an agent makes repeated actions within the environment but decreases as the actions become varied.

With α_i restricted to the range 0.1 to 1, there are three possible adjustments to the learning coefficient:

1. $\alpha_i(t+1) = \alpha_i(t) + 0.10$, if $(S(t) = S(t-1))$ and $(S(t-1) = S(t-2))$
2. $\alpha_i(t+1) = \alpha_i(t) + 0.05$, if $(S(t) = S(t-1))$ and $(S(t-1) \neq S(t-2))$
3. $\alpha_i(t+1) = \alpha_i(t) - 0.05$, if $(S(t) \neq S(t-1))$

Consequently, the probability of cooperation for agent *i* at time *t+1* is:

$$p(t+1) = p_{ei}(t) + (1-p_{ei}(t)) * \alpha_i, \text{ if at time } t, \text{ action} = C \text{ and } RP_{wt} > 0 \tag{7.11}$$
$$p(t+1) = (1-\alpha_i) * p_{ei}(t), \text{ if at time } t, \text{ action} = C \text{ and } RP_{wt} \leq 0 \tag{7.12}$$

The probability of defection is thus computed as $q_{ei}(t) = 1 - p_{ei}(t)$.

The same set of equations is also used for updating the action probabilities when the previous action is D:

$$q(t+1) = q_{ei}(t) + (1- q_{ei}(t)) * \alpha_i, \text{ if at time } t, \text{ action} = D \text{ and } RP_{wt} > 0 \tag{7.13}$$
$$q(t+1) = (1-\alpha_i) * q_{ei}(t), \text{ if at time } t, \text{ action} = D, \text{ and } RP_{wt} \leq 0 \tag{7.14}$$

The state of agent *i* is updated contingent on its previous state, the average neighbourhood production function, and the probabilities for both C and D. The neighbourhood production function for time t is the cooperation payoff for the group computed as:

$$pf_i = \sum_{i}^{3} Cj / N \tag{7.15}$$

where C_j is the payoff value for agent j and N is the total number of agents in the neighbourhood.

The average neighbourhood function for three memory events is formulated as:

$$\mathrm{pf}_{avg} = \frac{\sum_{i}^{3} pf_i}{3} \tag{7.16}$$

Thus, the state of agent *i* at time *t+1* with S(*t*):

For S(*t*) = C:

$$S(t+1) = \left\{ \frac{\text{D, if } RP_{wt} \text{ for agent i} < pf_{avg} \text{ and } p(t+1) < q(t+1) \text{ and } q(t+1) > R_u}{\text{C, retain previous action if the conditions for D are not satisfied}} \right\} \tag{7.17}$$

For S(*t*) = D:

$$S(t+1) = \left\{ \frac{\text{C, if } RP_{wt} \text{ for agent i} < pf_{avg} \text{ and } q(t+1) < p(t+1) \text{ and } p(t+1) > R_u}{\text{D, retain previous action if the conditions for C are not satisfied}} \right\} \tag{7.18}$$

,where $R_u \in [0,1]$ is a uniform random value.

7.4.3.3 Rule Based Inference of Affective States Post-Action Choice NPPD

The rule-base for the post-action choice NPPD affiliation emotions sets their intensities relative to the short-term, middle-term, and long-term valenced reactions to a NPPD result. The reader is once again directed to appendix 1 to view the hierarchical structure of these emotions.

The affiliation emotions are the most influential short-term reactions for the agent-based modeling of cooperation, because admiration and reproach are activated according to the appraisal of the actions of an agent's neighbours during game play. Within the affective framework, agents are naturally selfish automata who experience the attribution emotions in much the same manner as the well being prospect-based emotions; the higher the percentage of cooperators in a social grouping, the larger the payoff received. Fluctuations in cooperation composition are likely for neighbourhoods with a high percentage of total cooperators, because the temptation of agents to defect would surpass the benevolent considerations for the other citizens. However, an emotional agent will tend to cooperate with those neighbours he has a social connection with, which is contingent on the cognitive strength of the neighbourhood. By interacting with the same neighbours continually for a minimum of three NPPD events, the memory capabilities of the agents will produce a familiarity and awareness of altruistic tendencies in the social unit, and this facilitates the evaluation of the approving or disapproving affects of neighbourhood cooperation dynamics.

Anger is derived from the conjunction of the negative conditions of distress with reproach. The intensity of anger depends first on an agent's reaction to receiving a penalty, and then on the amount of blame placed on the decisions of others. Being partially derived from an affiliation emotion, context preservation is a necessary condition for the intensity of anger to be significant, because the distress of a negative payoff derived from the action choices of a grouping of trusted neighbours results in a compounded negative short-term affective state.

The post action choice emotions are also influenced by mood and personality with their intensities adjusted by mood class and neuroticism level. Mood class can be either positive or negative and is derived from the PAD spacing. As a positive emotion, the intensity of admiration is randomly increased (see appendix 1) with a positive mood class and decreased with a negative mood class. Reproach is a negative emotion, so the contrary adjustment is in place for these affective responses. The mood and personality adjustment for anger are embedded in the increases or decreases for distress and reproach so a secondary readjustment is unnecessary.

The long-term affect of neuroticism again influences the intensity of the emotion in situations where the emotional responses and mood state are neutral. For agents with high values of neuroticism in their OCEAN personality schema, the intensity of admiration from a neutral payoff is reduced while the intensities of reproach is increased in the same manner as the pre-NPPD emotions

7.4.4 Mood Adjustment

The last procedure in a simulation run is the adjustment of the mood spacing considering the intensities of all the activated emotions. This is an important element of the model, because it provides a methodological linkage to all of the NPPD emotions. A comprehensive short-term summary is transferred to a middle-term affective state at time *t*, either positive or negative, and is utilized in evaluating the pre-payoff NPPD emotions at time *t+1*.

The mapping of OCC emotions to Mehrabian PAD spacing models mood changes from an agent's comprehensive affective profile. Kessler *et al.* (2008)

present a mood updating component of the SIMPLEX emotion model that determines a mood state according to the average intensities of all activated emotions. The same approach is applied in this model as a function that computes an average PAD spacing from the intensities of the triggered emotions from the result of a NPPD event. Table 7.4 shows the comprehensive mapping of the OCC emotions and PAD space used in this research. The mathematical workings for the mood adjustment are found in appendix 2.

Table 7.4: Mapping of OCC Emotions to Mehrabian PAD Spacing for NPPD Events

Emotion	**P**leasure	**A**rousal	**D**ominance	**PAD** Octant	Mood Type	Mood Class
Joy	0.40	0.20	0.10	+P+A+D	Exuberant	Positive
Hope	0.20	0.20	-0.10	+P+A-D	Dependent	Positive
Relief	0.20	-0.30	0.40	+P-A+D	Relaxed	Positive
Admiration	0.40	0.30	-0.24	+P+A-D	Dependent	Positive
Distress	-0.40	-0.20	-0.50	-P-A-D	Bored	Negative
Fear	-0.64	0.60	-0.43	-P+A-D	Anxious	Negative
Reproach	-0.30	-0.10	0.40	-P-A+D	Disdainful	Negative
Anger	-0.51	0.59	0.25	-P+A+D	Hostile	Negative

7.5 The Model Environment

This paper is the continuance of research of this author about the spatial agent-based modeling of N-Person Prisoner's Dilemma (Power 2009). Thus, it is expected that the previous findings of the importance of context preservation and agent mobility on communal cooperation will be important processes during simulation events. However, this model also needs to consider the influence of the affective state of the agents on their action choices.

Figure 7.5 displays the interface of the model produced from a tight coupling with a layered model of affective NPPD and a Geographic Information System (GIS) and is designed to simulate the affectively influenced social interactions of mobile automata within an artificial environment. Context preservation can be analyzed by setting the length of time for each of the discrete choice activities during a simulation event. For example, the Work_Steps setting of 8 ensures that the agent remains at the work location for the preset number of social interactions.

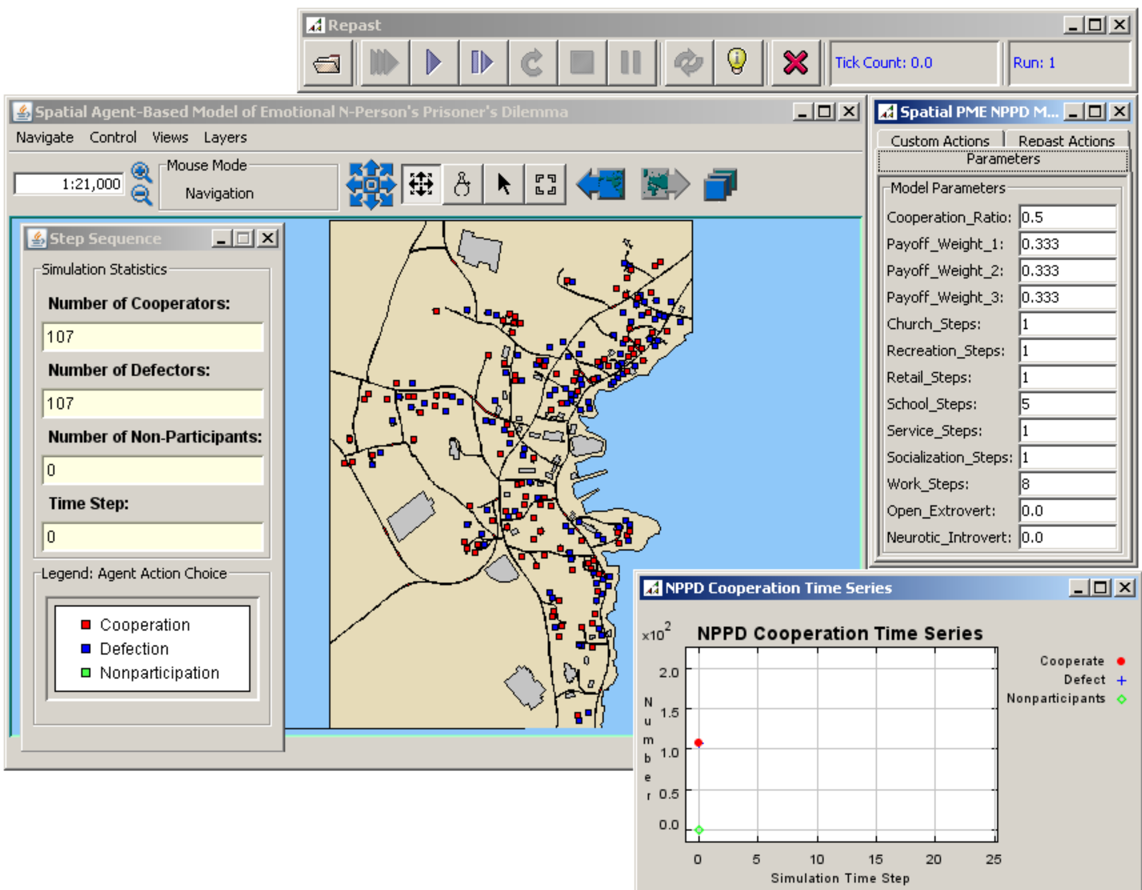

Figure 7.5: Model Interface

The mapping component in the center of figure 7.5 visually displays the spatial structure of the mobile trader agents and fixed non-mobile building automata in the environment. Locations of both types of agents follow a vector GIS geo-referencing convention. The building automata are polygons and the citizens are points, both imported into the GIS as ESRI© shapefiles. The relationship between both types of entities is hierarchical such that the point agents are spatially nested within the building automata. As an agent moves, the destination location is geo-referenced by pointing to a specific building object.

7.6 Model Experiments

An explicit modeling objective of the experiments is to determine how the mobility dynamics and affective state of the agents influence the emergence of cooperation in the environment. For all simulations, the mobility behaviors of the agents depend on the length of the time step settings for each possible activity, most set to 1 except school and work events, which are set to 5 and 8 time steps respectively. Cognitively, a time step is a set period of agent interactions, which are proxies for the amount of time that real people engage in these activities. For example, a retail event is an incidental social exchange that occurs within a single interaction between a customer and a retail employee

The stochastic elements in the model limit the insight from a single simulation result so 500 simulations, each with 500 time steps, were run for the initialization setting. Thus, the discussion about the experiment results is based on the most common mobility and cooperation action choices, and the average affective state patterns sampled at specific time steps.

Figure 7.6 graphs the average action choices for the agent population, and, at each time step, there are more defectors than cooperators throughout the entire environment. This is the expected pattern due to the utility functions assigning the highest payoffs to the defectors. The interesting pattern is the emergence of a subpopulation of agents who avoid participation in both mobility and NPPD events. These nonparticipants were given low setting of extraversion during the OCEAN personality assignment, which sets the condition that whenever the emotional and mood state are minimal for a time step, this personality trait increases the probability the agent will remain at their residence location and shun social contact. However, nonparticipation is limited to several instances at each time step so the social interaction network within the environment is minimally restricted.

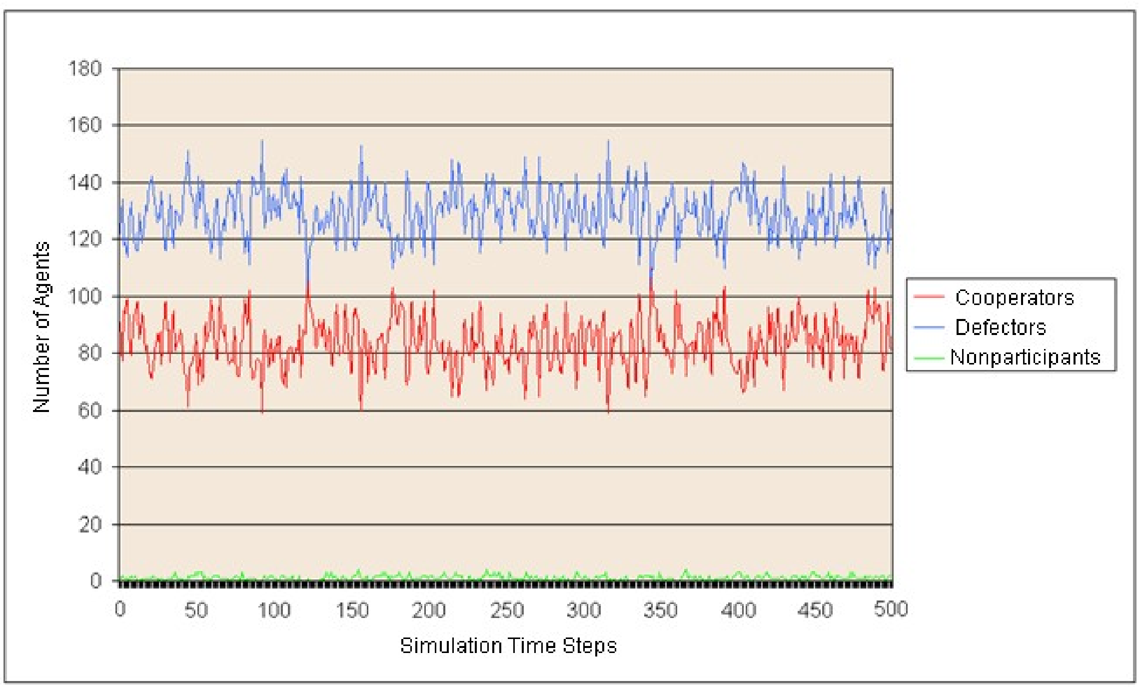

Figure 7.6: Simulation Summary of Action Choices for the Agent Population

Figure 7.7 contains a series of six maps that document that spatial dynamics of mobility and social interaction processes in the simulations. Sampled at successive intervals of 100 time steps, each map presents the most common location and action choice of each agent for the 500 simulations. From a randomly assigned starting population of an equal number of cooperators and defectors, spatial clusters of similar action choices emerge at the later time steps. To gauge the effect of agent mobility and context preservation on this spatial clustering, the locations of the places of

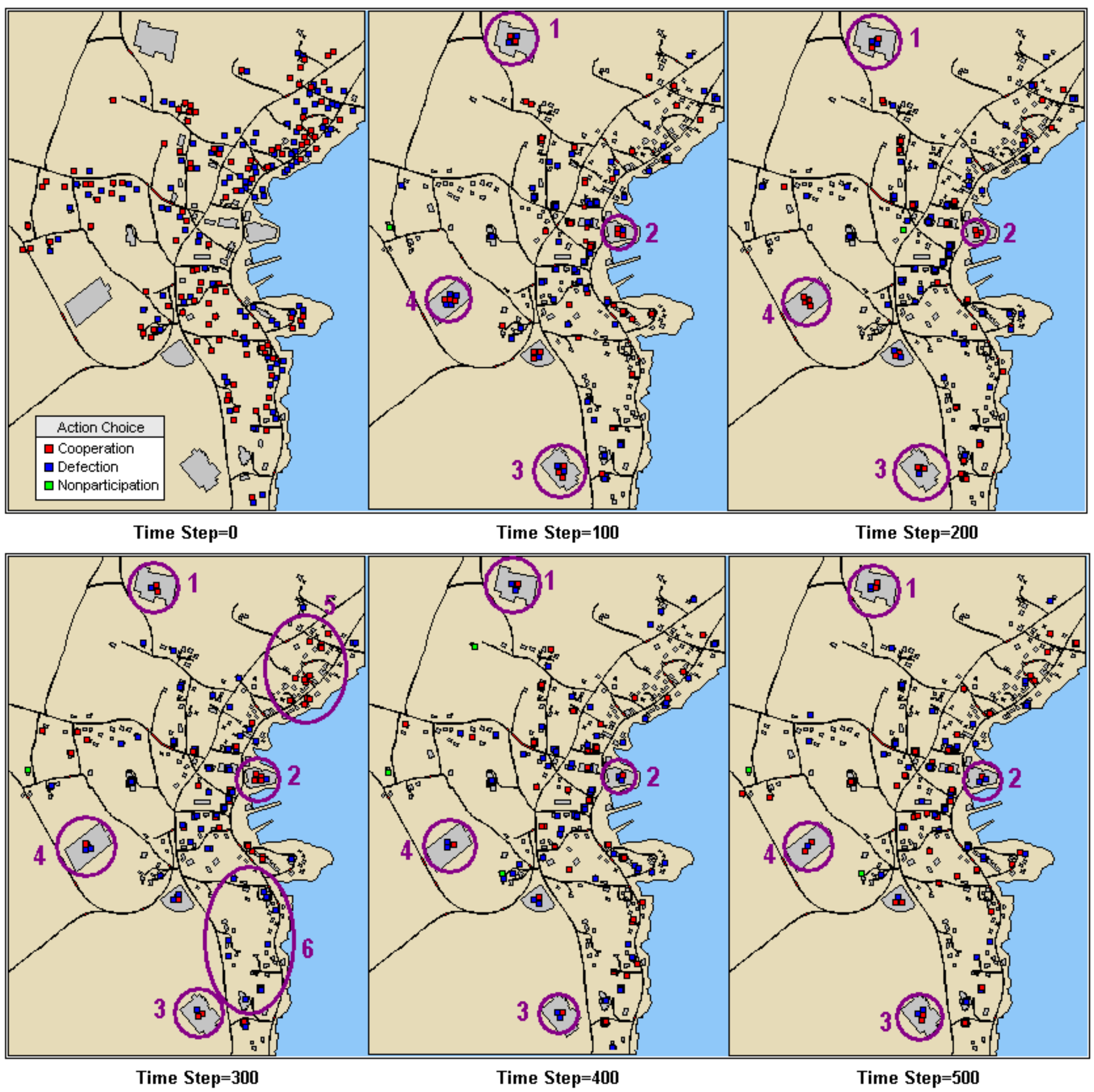

Figure 7.7: Simulation Results for the Spatial Agent Population

employment (numbered 1 to 3) and the school (4) are highlighted with purple ellipses. The neighbourhoods at these locations for time steps 100, 300, 400, and 500 have a blended structure of both cooperators and defectors, but there are homogeneous groupings of cooperators at locations 2 and 4 for time step 200. Power (2009) has determined that the strength of a "sense of familiarity" amongst a grouping of agentsdepends on the temporal constancy of the social network, which increases the probability of the emergence of a fully cooperative neighbourhood. Yet, blended action choice groupings indirectly indicate that the temptation of a high positive payoff available to a defector within a predominantly cooperative environment causes a portion of the agents to remain self-interested despite familiarity with their neighbours. Spatial clustering of both cooperation and defection can also emerge when context preservation is negligible as seen at locations 5 and 6 at time step 300. Since these agents pursue activities that require mobility events at each time step, the similarities in action choice are predicated on their affective states.

Figure 7.8 is a ring diagram of the average dominant emotion of the automata at each time step. The bins consist of six segments, the size of each representing the percentage of the total agent population who have experienced a specific highest intensity emotion the most often throughout the simulation runs. For example at time step 1, the most common intense emotional percentages are 25%, 26%, 38%, 6%, 2%, and 3% for hope, relief, joy, admiration, reproach, and anger respectively. Joy is the predominant short-term affect throughout the simulation runs, followed by hope and relief. The prevalence of joy indicates that most of agents are very pleased with the

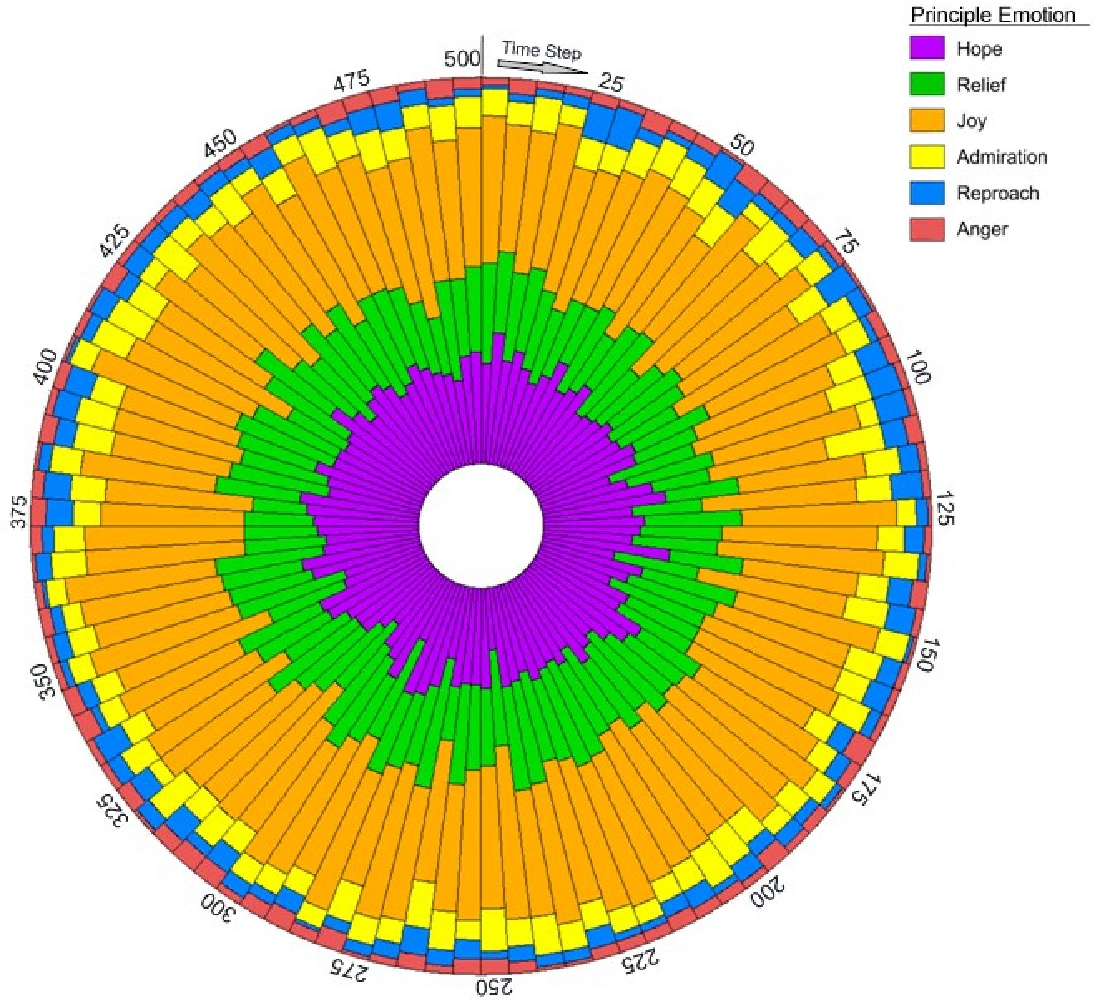

Figure 7.8: Ring Histogram of the Average Principle Emotion in the Simulations

outcomes of the NPPD events, but it also highlights their self-interested nature of being primarily concerned with obtaining a positive payoff at each social interaction. The affective presence of hope and relief is an interesting finding, because, despite one being a likelihood event-based emotion and the other a realization state, the strength of their intensities is often interrelated. It was established that when hope or relief is the most intense emotion, the agents have usually either just arrived at a work or school location to start the NPPD interaction period or undertaken a mobility event for a single time step stay period. The non-familiarity of the neighbourhood structure causes the agents to hope for a positive payoff, but they have a level of trepidation about a possible negative outcome. Once the NPPD event has produced a satisfactory result, the level of relief felt by the agent is significant. Therefore, the negligible influence of context preservation in this case is a condition for an interconnection between these two valenced reactions.

The opposite situation exists for both admiration and reproach, where context preservation plays a considerable role. When admiration or reproach is the most intense emotion, the agents are usually engaged in either a work or school activity event. The constant assignment of a positive payoff from a set of homophily automata causes an agent to appreciate the altruistic behaviors of his neighbours. However, any deviation from communal cooperation leading to a neutral or negative payoff is met with reproach. The longer the succession of positive payoffs followed by a negative result, the more intense the sense of reproach towards the neighbours. It is also these disgruntled agents who experience anger from both the selfish action choices in their social grouping and the distress of a negative payoff.

With the mood spacing of an agent set a three-step memory affective condition, the principle average temporal mood state provides a comprehensive and less sensitive interpretation of the affective condition of each agent during a set of simulation runs. Figure 7.9 is a ring diagram of the dominant average mood space for the simulation runs, with each time step containing bins for five PAD spacing assignments. It has a similar affective structure as figure 7.8 with a considerable portion of the population in an exuberant mood due to the positive results from the NPPD events. However, the prevalent mood space is dependent (+P+A-D) where the

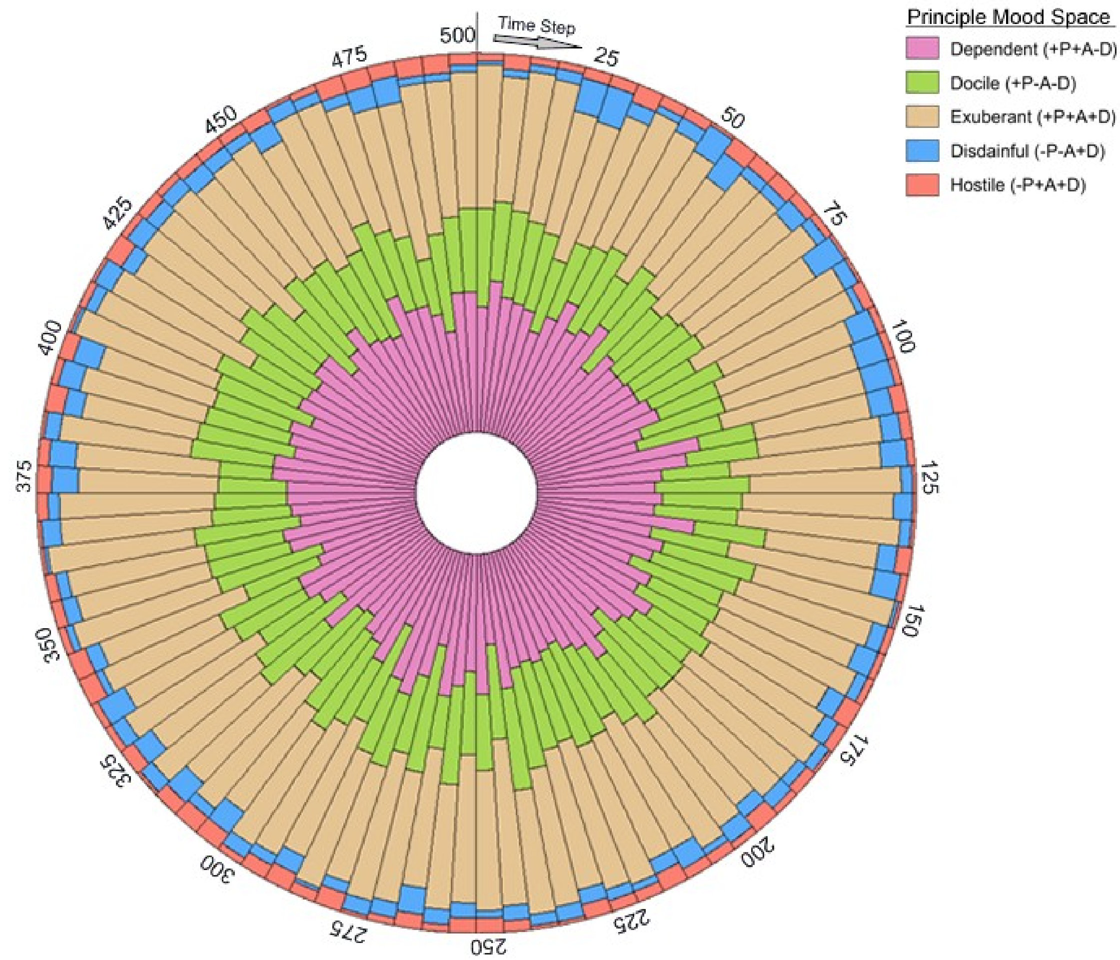

Figure 7.9: Ring Histogram of the Average Principle Mood Space in the Simulations

agents experience positive pleasure and arousal and negative dominance. A dependent mood space signifies that the agents experience a lack of control during a series of social interactions, but in a homophily environment, this suggests that they have become more inclined to be less selfish in favor of altruistic behaviours. The last two mood spacings comprise a small portion of each time step in the ring diagram, but disdainful and hostile signify the presence of uncooperative behaviors. Interestingly enough, context preservation is a requirement for these mood spacings, but in a negative sense. Agents that are either disdainful or hostile are displeased with their neighbours' continual selfishness so they resort to antisocial behavior to gain a degree of control within the grouping. This is further highlighted by the fact that these mood spacings were not an issue amongst neighbourhoods of agents engaged in single time step mobility events.of the population in an exuberant mood due to the positive results from the NPPD events. However, the prevalent mood space is dependent (+P+A-D) where agents experience positive pleasure and arousal and negative dominance. A dependent mood space signifies that the agents experience a lack of control during a series of social interactions, but in a homophily environment, this suggests that they have become more inclined to be less selfish in favor of altruistic behaviours. The last two mood spacings comprise a small portion of each time step in the ring diagram, but disdainful and hostile signify the presence of uncooperative behaviors. Interestingly enough, context preservation is a requirement for these mood spacings, but in a negative sense. Agents that are either disdainful or hostile are displeased with their neighbours' continual level of selfishness so they resort to antisocial behavior to gain a degree of control within the grouping. This is further highlighted by the fact that these mood spacings were not an issue amongst neighbourhoods of agents engaged in single time step mobility events.

7.7 Conclusion

This paper describes the methodology and structure of an integrated agent-based model of affective NPPD that simulates the emergence of cooperation in a synthesized socio-geographic environment. The integrated system has a spatial module to simulate mobility behaviors and neighbourhood confluences of agents, a

Personality-Mood-Emotions component to model the agent affective states, and a NPPD mechanism to simulate social interactions. This layered model of affect is designed to calculate the intensities of the triggered emotions from the outcome of NPPD events and to adjust the intensities relative to agent temporal mood state and personality.

The simulation runs investigate how the mobility behaviors and affective profile of an agent influences the emergence of cooperation. Analysis of the average dominant emotional states indicates that joy was the most common short-term affective response to the NPPD results. Social agents are naturally self-interested so any interaction that is personally beneficial and pleasing is positively received. The expected role of context preservation and neighbourhood strength in the multiple time step NPPD events emerged, but with both positive and negative connotations. On the positive side, admiration was the average dominant emotion of agents who appreciate and affectively recognize the altruistic decisions of their neighbours. Reproach and anger were negatively experienced by individuals who decide to cooperate in the social groupings but were constantly frustrated with the selfish action choices of their neighbours. The middle term affective states of the agents during the simulation runs show that joyous individuals tend to transition into exuberant mood state over the three-step memory period. However, the most prevalent average temporal mood state is dependence, where the agent experiences a lack of control in the social interaction. In familiar neighbourhoods, there is a stage in the game play where individuals will relinquish their self-interested control to make altruistic decisions that benefit the entire grouping, and they remain in this cooperative mindset throughout the activity interaction period. This process explains the emergence of spatial clusters of cooperators at the school and work places, which are the locations initialized for multiple time step NPPD interactions.

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8.0 Paper 3: Spatial Agent-Based Modeling of an Evolutionary Labour Market Game

Abstract

The objective of this paper is to present a spatially explicit agent-based model of an evolutionary labour market game that builds on the methodology of Trade Network Game research by including an employee mobility mechanism to simulate directed work flows. The theoretical benefit of adding labour market mobility to the original formalization is that the distance that each employee must travel to each firm could influence their social interaction decisions and matching partnerships with the firms. In terms of specifications, the model is comprised of mechanisms for the geographically influenced preferential partnership matching, Iterative Prisoner's Dilemma market exchanges, the genetic evolution of successful worksite strategies, and spatially constrained action strategy diffusion. The system simulates the emergence of cooperation within a market environment from the mobility and socialization decisions of the individuals as they engage in worksite interactions.

Simulation runs investigate the influence of a non-employment payment and the distance between employees and firms on the emergence of preferential partnerships, labour market participation rates, and worksite choices. The significance of place is evident with the results from a high non-employment payment-high distance cost simulation. The social network of firm-employee relationships self-organizes into a smaller group of the most distant firms connected to the geographically closest employees.

8.1 Introduction

The field of agent-based computational economics is being advanced as an alternative modeling framework for investigating the dynamics of labour market and economic interactions. Departing from the empirical statistical top-down methods, agent-based computational economics is a bottom-up nonlinear approach that models markets as systems of autonomous interacting socio-economic entities. The goal of many models is to understand the emergent global patterns and regularities in economic processes, which arise from path-dependent decisions and behaviors of individual agents.

Tesfatsion (2002) provides a comprehensive survey of agent-based computational economics research of complex adaptive systems dealing with the evolution of behavioral norms, formation of economic networks, etc. For this study, research on the formation of economic networks is topical, specifically the means of agent selection of partners in labour market transactions. Klos and Nooteboom (2001) developed a preferential relationship model that simulates the affiliation between buyer and supplier firms that depends on anticipated future returns. A consideration of the work is the emergence of trust between agents based on expected benefits and the effect of the duration of a relationship on the level of trust.

Studies on the formation of trade networks also demonstrate the value of agent-based modeling in labour market simulations. Several authors (Tesfatsion, 1997; 1998; 2001; McFadzean and Tesfatsion, 1999; Pingle and Tesfatsion, 2001) present an agent-based framework for modeling labour markets as Trade Network Games (TNG). The aim of a TNG simulation is to study the evolutionary and emergent structure of preferential partner selection between agents and to model the dynamics of social interactions under varied market conditions. For example, TNG models have simulated employee-employer social networks (Smucker, Stanley, and Ashlock, 1994; Kitcher, 1998), and the evolutionary dynamics of social welfare (Hauk, 2001). Tesfatsion (1997) provides the founding methodology of a TNG model for endogenous partner selection in a labour market environment. Throughout a simulation event, employees and firms engage in two activities: (1) determining preferential partnerships with a modified Gale and Shapley (1962) matching routine, where individuals are paired according to the expected payoffs that each agent associates with all potential partners, and (2) an employment process where a pairing of agents undertakes social interactions as an Iterative Prisoner’s Dilemma game. For both processes, each agent updates his current utility assessment with a potential partner each time he obtains a payoff. The distinctive feature of a matching procedure is that employee-firm pairings are not randomly determined or set by a deterministic mechanism, such as a grid neighborhood (Ashlock, Smucker, Stanley, and Tesfatsion, 1996). Instead, a preferential partnership mechanism ensures that employees direct work offers to firms they believe they can have a cooperative social exchange with, and these firms utilize the same assessment process to either accept or reject the offer. Throughout a simulation time step, employees develop assessments about the preferable firms they make offers to, and the firms form assessments about the more preferable workers they accept offers from. The matching process continues until the resultant pairings are core stable and Pareto optimized in that every trader is at least as well off as the other agents and at least one individual is better off in terms of expected payoffs. In other words, the matching arrangement can not be improved without negatively impacting at least one agent. The agents then engage in the dyadic interaction as an Iterative Prisoner's Dilemma simulation of the progression of a cooperative or defective relationship between the partners. A final step in a trade time step is an evolutionary procedure of social mimicry where the less successful (lowest paid) agents adjust their worksite rules by copying the strategies of their highest paid neighbours.

Stanley, Ashlock, and Tesfatsion (1994) developed a similar labour market model with a preferential partnership matching mechanism to conduct simulations of employee-firm social networks. Agents were determined to choose partners that they believe will cooperate with them, which produced long-term relational networks of nice agents. The principle finding is that agent matching resulted in the emergence of cooperative behaviors quicker than a random iterative pairing procedure.

Pingle and Tesfatsion (2001) experimented with the effect of a non-employment payoff on the evolution of cooperation between workers and firms in a labour market game with incomplete contracts. The non-employment payoff is an interesting modeling parameter, because, depending on the amount, agents may decide to collect an unemployment payment and not participate in the labour market. Results for simulation runs for zero, low, and high non-employment payoff values reveal that increases in the non-employment payoff result in higher unemployment and vacancy rates while at the same time encouraging higher rates of cooperation among the matched workers and employers. Increasing the non-employment payoff also filters outs firms and workers more likely to defect, and this translates into higher productivity and social welfare levels. This suggests that the labour market participants learn to coordinate their behaviors as cooperative strategies, thus improving the overall efficiency of the simulated labour market.

An additional expansion of the TNG approach that has not been extensively explored to this point is the effect of place on the emergence of preferential partnerships and labour market structure. It is hypothesized that the spatial locations of the residences of the agents will influence the diffusion of the successful work strategy information throughout the environment, and that the distances that an employee must travel to get to a firm plays a similar role as the non-employment payment in the matching and employment processes of a labour market model.

The objective of this paper is to present a spatial agent-based model of an evolutionary labour market game that builds on the research of Tesfatsion (1997) by including a mobility mechanism to simulate employee work flows. The theoretical benefit of labour market mobility is that a distance cost (e.g. public transportation, rising fuel cost, automobile operation, etc.) that an employee will incur to travel to a firm could influence their behavioral decisions and matching partnerships with the firms. Mobility cost is set as a negative payoff that increases with the distance between the employee and firm, and is included as a penalty adjustment to the cumulative payoff for each labour market interaction cycle. During the initial stages of a simulation time step with all things being equal relative to expected payoffs, firms that are closer to the employees should receive more directed work offers than those farther away, but the temporal constancy of this offer submission pattern needs to be investigated. The emergence of distinct employee-firm interaction networks can also be place dependent, because the employment instability of receiving few or no work offers may bias the remote firms towards cooperative decisions with employees. The contrary consideration is the propensity of closer firms with many work offers to engage in exploitive behaviors. Relationality in the social interaction system is reliant on the spatial confluence of social networks of preferential partnerships in the environment and the diffusion of work strategy information among the agents. It is speculated that the level of communal cooperation, measured as social welfare (Orbell and Dawes, 1993), and the social mimicry of work strategies will be influenced by changes in the size and geographic extent of interaction neighborhoods, either due to varied initialization parameters or emergent processes during a simulation event.

The paper begins with a discussion of the methodology of the spatial labour market game. This consists of a preferential partner matching process, Iterative Prisoner's Dilemma employment process, genetic evolution of worksite strategies, and the spatially influenced social mimicry of successful action strategies. Attention will be directed to the function of place and employee mobility in the implementation of the model components. The discussion of the methodology gives an overview of the basic architecture of the model. Support for the methodology is given by simulations results with varied non-employment payoffs and distance cost penalties.

8.2 Methodology

The methodology of the spatial agent-based labour market game is founded on the general formalization of Tesfatsion (1997), and the reader is referred to

McFadzean and Tesfatsion (1999) for a detailed overview of the components of the standard model. The architecture of Tesfatsion's model is expanded by the inclusion of four spatially explicit mechanisms in the labour market processes. Firstly, an employee-firm matching routine is utilized by the agents to evaluate their potential listing of interaction partners according to expected payoffs. A consideration in this process of preferential partnering is the distance cost that an employee incurs as he travels to a firm location to submit a work offer. Since the distance cost is subtracted from the expected payoff, the submission of work offers can often be locally contained. The second component is the Iterative Prisoner's Dilemma game, where each employee-firm pairing in a spatially defined network engages in rounds of social exchanges. Thirdly, an evolutionary learning module is implemented as a genetic algorithm to produce successful action strategies from the pairings of highest paid agents. Lastly, an action strategy diffusion mechanism identifies the lowest and highest paid agents in a geographic neighbourhood, and instructs the less successful agent to imitate the action strategies of his more successful neighbour.

The modeling procedure for each simulation time step can be viewed as a sequence of activities that comprise a typical labour market day. At the start of each day, the employees and firms develop a mental listing of potential labour market partners from the expected payoffs that are associated with these people. The expected payoff is the financial reward that an agent believes he will get from an interaction with a specific individual during a labour market exchange. The agents refer to past successful transactions to estimate the amount of expected payoffs attached to the labour market partners. However, employees must also adjust their expected payoffs by considering the cost of traveling to the firm locations and any penalties associated with a work offer.

The second event in a labour market day is the movement of employees to the most preferred firms to submit an offer to work, the identification of the composition of employees within a firm's neighbourhood, and the firm's evaluation of the work offers of the employees. Each work offer is considered individually as the firm first determines if this potential employee is in his listing of preferred workers, which is an inventory of the agents that the firm has a memory of obtaining a positive payoff from the previous interactions between them. The employees that are ranked the highest in the firm's worker listing are told that they are accepted as prospective partners in the labour market game. The work offers from the other employees not on the firm listing are rejected, and these unsatisfied workers move to the next preferred firm, and the model performs the same work offer and firm evaluation process. This continues until the employees have either traveled to and submitted work offers to all of the firms or have willing left the labour market and accepted an unemployment payment.

The third stage of the labour market day is the actual labour market transactions between the firms and their preferred employees. Formally, this requires a set of nested interactions of labour market communications and learning within the simulation time step. These interactions are referred to as generations of labour market exchanges, because the end result of each interaction is a new generation of behavioral strategies that are diffused to the lowest paid labour market participants. Each generation proceeds in the following manner. First, the firm will engage in a

Prisoner's Dilemma interaction with each employee within his neighbourhood. Secondly, after the firm has interacted with each employee, the workers talk amongst themselves to determine who received the highest payments from the labour market exchange. The third step is the central procedure of a generation, the evolutionary adaptation of successful action strategies and learning by the unsatisfied agents. Two individuals are probabilistically selected from a grouping of the higher paid agents, and their action strategies are genetically altered to generate an offspring strategy that is more likely to give the highest payoff in the labour market interactions within this neighbourhood. The lowest paid agent wants to improve his result in the next labour market generation so he proceeds with a process of social mimicry where he discards his own action strategy and imitates the optimized offspring strategy. All of the other agents retain their action strategies for the next generation of labour market interactions. For each simulation time step, this three stage process of labour market interactions is simulated for g_r rounds, where g_r is the parameter setting specifying the number of labour market generations.

The fourth stage of a labour market day is a second movement event of the employees to their residence locations after work, and the estimation of the agent composition of each employee neighbourhood. The residential neighbourhoods are the relational networks for the final stage of a labour market day, which is the social mimicry of the action strategy of the highest paid neighbour by the least successful neighbour. The benefit of this supplementary application of social mimicry is that the unsatisfied agents can be exposed to the action strategies that were successful at firm locations other than where they were situated for time t. The lowest paid agent sets his behavioral schema to the action strategy of the most satisfied neighbour to improve his likelihood of a better performance in the next simulation time step.

The application of the model will simulate a two-sided labour market in an unstructured environment of adaptive firms and employees who have the option of non-employment. In the two-sided market, the set of *b* employees (agents who submit work offers) is disjoint from the set of *s* firms (agents who receive work offers). Therefore, the market structure is the union $V = B \cup S$ of the B subset of employees and the S subset of firms, where the employees can have up to *bq* work offers to the firms and the firms can accept no more than *sq* work offers from the employees, where *bq* and *sq* are parameters representing an offer quota and an acceptance quota respectively. For an interaction cycle, each employee and firm is randomly assigned initial expected payoffs for each of its potential partners and a preliminary worksite action strategy. A common choice in the standard framework is to set these utility levels equal to the mutual cooperation payoff from the Prisoner's Dilemma payoff matrix. For this study, the expected payoffs that the firms have for each employee are set in the same manner, but the expected payoffs that the employees have for each firm must take into consideration the distance between them. Thus, the expected payoffs that each employee has for the *n* firms are set by adjusting the mutual cooperation payoff by a random amount ± 0.1. When the *n* firms have the same expected utility payoff, each employee will usually default to the nearest firm to pay the lowest distance cost. However, the assignment of different expected payoffs to each firm for the employees ensures that the farthest away firms receive work offers at the start of the interaction cycle and are not isolated from the market exchanges.

The action strategy of each agent determines its behaviour in worksite interactions. From Miller (1994), each worksite action strategy is a randomly generated finite state machine that is computationally represented as a Moore Machine with sixteen internal states. A Moore Machine developed to play the Iterative Prisoner's Dilemma will consist of four elements. The first feature is a set of internal states, one of which is set as the starting or initial state of the Moore Machine; this initial state is the second element. Thirdly, each state has a specific action associated with it, so for the Iterative Prisoner's Dilemma, it indicates whether the machine will cooperate (C) or defect (D) at time $t+1$. The final element is a transition function linked to each internal state that determines the next state given the action choice of the opponent. The transitions may go to any of the internal states (including the current one), and are always conditioned on the current state of the machine and the reported move of the opponent. Thus, a machine begins in its starting state and does the action specified in that state (either C or D). The machine then moves to a new internal state based on the observed move of the opponent, and proceeds with the action specified in the new state. This process will continue until the game ends.

A more intuitive description of a finite state machine is given by its transition diagram (see Figure 8.1). The circles in the transition diagram represent the internal states, and the upper-case labels inside of the circles indicate the action choice of the machine when it enters this state. The labeled arcs extending from the circles are transition functions, with the lower-case labels representing the observed action of the opponent and the arc direction the machine's next state. As an illustration, the finite state machine in Figure 8.1 is a deterministic model of Tit-for-Tat. Starting with C in the left-hand state, the machine cooperates again at time *t+1*. After a defection from the opponent, a transition is triggered to the right-hand state and the machine issues a defection D. The automaton will remain in the right-hand state (and thereby continue

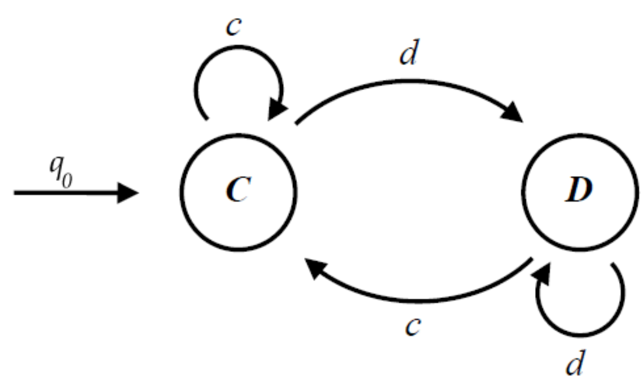

Figure 8.1: Finite State Transition Diagram for Tit-For-Tat

defecting) until a cooperation is observed by the opponent, at which time a transition to the left-hand cooperative state occurs.

Each Moore Machine is represented by a binary coded decimal numeric string of 148 bits (Hardy and Steeb, 2001). The first four bits provide the starting state of the agent. Sixteen nine-bit bundles are positioned in a string array, and each represents an internal state of the automaton (see Figure 8.2). The first bit in the bundle sets the move at time *t+1* whenever the automaton is in that state (0=cooperate, 1=defect). The following four bits dictate the transition state when the opponent cooperates, and the final four bits give the transition state if a defection is observed.

The preferential partnership process is a spatially modified Gale-Shapley matching mechanism. With an unstructured environment of more employees than firms, the matching process is a (many to one match) college admission game rather than the (one to one match) core marriage game (Roth and Sotomayor, 1992). The spatial influence is to amend the expected payoffs assigned to each firm for each employee, by creating a spatially adjusted expected payoff that subtracts the distance cost from the original expected payoff.

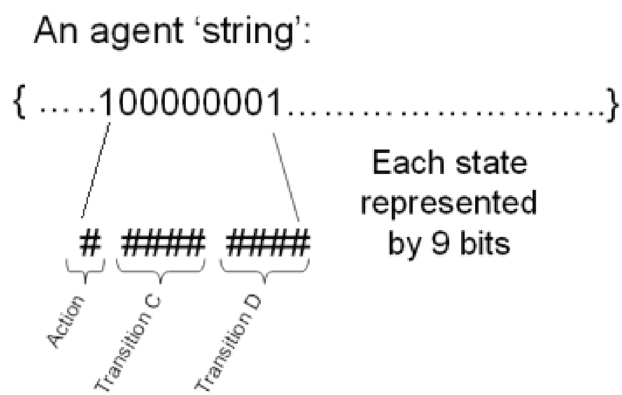

Figure 8.2: Example of Part of a Bit-String used to Represent a State in an Agent's Strategy

For any agent *v* in V, *v* uses the expected payoffs $U_v(k)$ in the preferential partnering mechanism to determine the offering, acceptance, and refusal of interaction offers based on the ranking of potential partners *k*. The spatial influence on $U_v(k)$ is dependent on the distance between *v* and *k*, the mobility status of *v*, and the neighborhood structure of *k*. A condition of the matching procedure is that agents have to be in close spatial proximity to submit work offers, which requires a movement event by an employee agent. Movement is penalized with a negative payoff *dc* that is subtracted from $U_v(k)$ to produce a spatially adjusted expected payoff value $Us_v(k)$. In this model, the firms are fixed agents while the employees are mobile agents. Therefore, the distance cost for firms is zero so their $Us_v(k) =$ $U_v(k)$. For the employees, *dc* is computed as:

$$dc = \frac{Db_i(k)}{Max\,D_{bs}}, \tag{8.1}$$

where *i* is the current location of agent *b*, $Db_i(k)$ is the road distance between agents *b* and *k*, and $Max\,D_{bs}$ is the maximum road distance between an employee and a firm calculated during initialization.

The manner in which worksite interactions are directed also depends on the tolerability of the partnership between agents, expressed as the minimum tolerance level. As is standard, the minimum tolerance level is set to 0 so that work offers are not directed with $Us_v(k) < 0$. When $Us_v(k) \geq 0$, each employee submits up to *bq* work offers to the tolerable firms, beginning with the firm with the highest $Us_v(k)$ value.

The labour market mechanisms are dynamically coupled to a Geographic Information System (GIS) to handle the spatial dynamics of the model. An important factor of representing labour market agents in a GIS context is that movement can produce a change in the vector geometry and topology of the agent population. Consequently, it is necessary for firm *s* to geographically identify the employees that are situated within a confluence neighbourhood. During a simulation, the agent composition of the neighborhood for *s* is estimated with a GIS buffer operation. Formally, a buffer of a specified radius (a model parameter) is drawn around the point location of each firm agent, and a point-in-polygon method identifies those agents that fall within the buffered area and classifies them as neighbors.

The employees within the matching neighborhood have determined that firm *s* is the most preferred employer at this stage of the matching process. As fixed agents, firms make no direct evaluation of employees before they are determined suitable according to the ranking of highest expected payoffs. Once judged, firm *s*'s most preferred employees are placed on a waitlist of employee objects while the remaining employee neighbors are rejected by *s* and penalized a negative transaction cost payoff. A principle of the spatial labour market game is that the rejected neighbors have to move from the location of the dismissive firm before the neighborhood composition can be computed for matching step $m+1$. Therefore, each rejected worker moves to the geographic location of the next most preferred tolerable firm who has not rejected him in the matching process and submits a work offer. If no tolerable firm exists, the employee returns to his residence, pays a distance cost from firm s_m to his residence, and takes the non-employment payment. As before, the expected payoff is adjusted according to the offer cost and distance cost *dc*, but, for matching step m > 1, *dc* is relative to the distance from firm *m* to firm *m*+1. The more instances that an employee pays offer costs, and refusal and distance penalties, the more likely he is to return to his place of residence and accept the non-employment payment.

This matching process continues until firms stop receiving new work offers, and the prospective employees on their waitlist are accepted for the employment negotiation process. All other employees who have submitted at least one work offer are excluded from the interaction network as the mobility mechanism returns them to their place of residence and assigns them the non-employment payment.

With the completion of the matching procedure and the preferential partnerships sets, the generations of labour market interactions between each firm and the employees in its waitlist begins. Each pairing of employee and firm represents a mutually agreed upon interaction between labour market agents that is simulated as an Iterative Prisoner's Dilemma game for that work cycle. Originating within the field of game theory, the Prisoner's Dilemma is a type of non-zero sum game played by two players who can choose between two moves, either to cooperate with or defect from the other player. The key tenet of this game is that the only concern of each individual player is to maximize his payoff during the interaction, with the size of the reward or penalty determined from a payoff matrix (Table 8.1). The dilemma arises when a selfish player realizes that he cannot make a good choice without knowing what the other one will do.

Table 8.1: Payoff Matrix for the Spatial Labour Market Prisoner's Dilemma Game

	Player A (Firm)		
		Cooperate	Defect
Player B (Employee)	Cooperate	1.4, 1.4	-1.6, 3.4
	Defect	3.4, -1.6	-0.6, -0.6

An agent's action strategy is an autonomous schema that is unknown to the other agents before game play. During a game play simulation round, agents only learn about their opponent's strategy by observing their actions and evaluating the derived payoffs. So, an agent's action choice (C or D) for a labour market event is based entirely on the history with an opponent so the agent must keep track of the current state associated with each potential partner.

During the course of each game play round, agents use a simple criterion filter to update their expected utility assessments for their potential partners as new utility payoffs are received. The criterion filter uses a payoff count $N_V(k)$ and memory weight $w_V(k)$ to adjust $Us_v(k)$ of agent v with partner k according to interaction payoffs or refusal penalties. After each social exchange between v and k, the current payoff count is set as (McFadzean and Tesfatsion, (1999)):

$$N_V(k)= N_V(k) + 1 \tag{8.2}$$

to revise the memory weight

$$w_V(k)= N_V(k) \,/\, [N_V(k) + 1] \tag{8.3}$$

The expected payoff $Us_v(k)$ that v links to k is then updated as

$$Us_v(k) = w_V(k)\ Us_v(k) + [1- w_V(k)]P, \tag{8.4}$$

where P is the payoff or refusal penalty from the current interaction between the partners.

The function of the criterion filter is to ensure that the expected payoff that agent v associates with agent k approaches the true average payoff that v would get from limitless repeated interactions with k. In the absence of high positive payoffs, the weighting mechanism sets the condition where repeated refusal payoffs will lower the expected payoff associated with an agent to a value less than the minimum tolerance level, thus leading to termination of the current labour market interaction.

At the end of each game play round, the action strategies of the agents evolve according to fitness scores. Formally, a genetic algorithm utilizes elitism, crossover, and mutation to retain the most successful strategies of the agents with the highest payoffs while replacing the strategies of all other agents with variants of these successful finite state machines. Figure 8.3 displays the general structure of the genetic algorithm consisting of encoding and representation, parent selection, and generation of optimized action strategies with genetic operators.

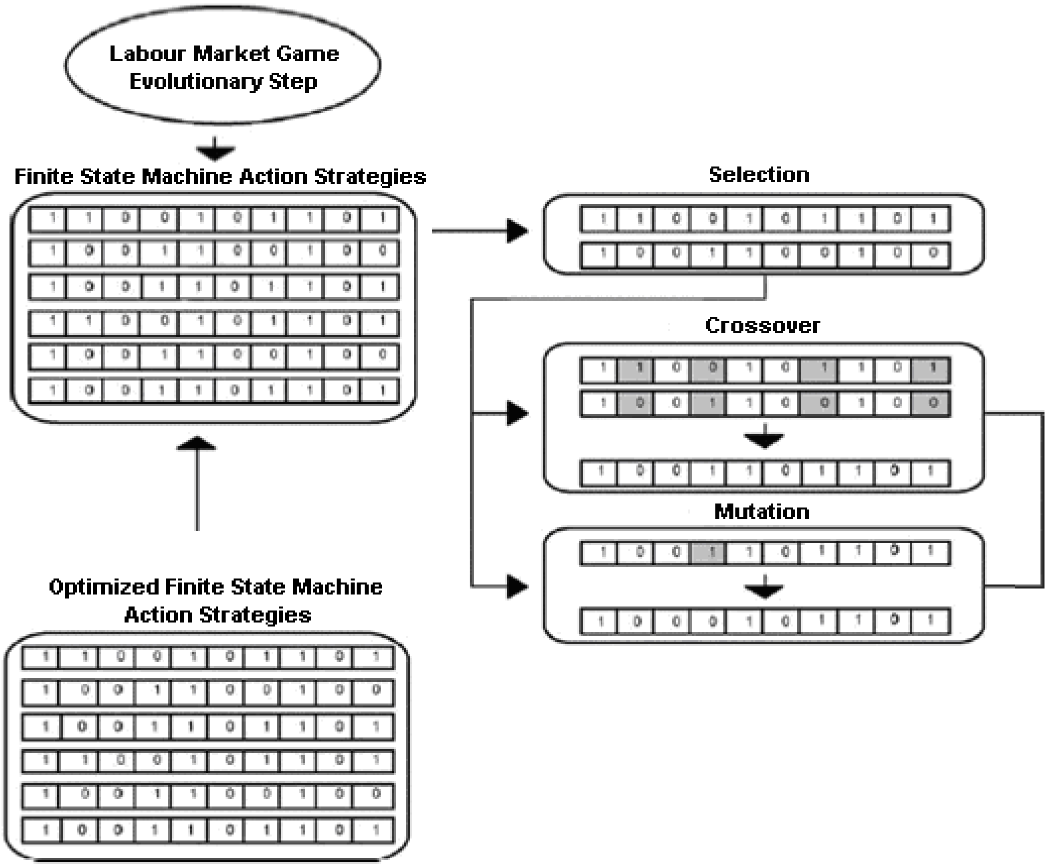

Figure 8.3: The Functional Implementation of the Elements in the Genetic Algorithm

Moore Machine action strategies are encoded as genetic chromosomes for both employees and firms in the model. Depending on the initialized percentage of highest paid agents that comprise a subpopulation of successful agents, *n* pairs of these agents are probabilistically selected as parents for the evolutionary process. The probability of selection is proportional to the actual payoffs from the employment events for a particular round of game play, so the higher the payoff for an agent, the greater the chance that it will be chosen as a parent for the evolutionary step. In a standard genetic algorithm, two parent agents reproduce, and their chromosomes are altered to generate optimized action strategies. Firstly, elitism ensures that each of the original action strategies is preserved for the next interaction cycle before the parents engage in the genetic process. Next, crossover and mutation are the operators that produce the optimized worksite strategies**.**

Crossover is a process that emulates sexual reproduction by recombining alleles through the exchanging of segments between pairs of chromosomes (Hosage and Goodchild, 1986). The standard two point crossover of parent pairs involves randomly selecting two bit positions on the finite state machine string of the first parent, and exchanging the corresponding bit string with those of the second parent to obtain an offspring Moore Machine action strategy.

Mutation is a process that alters the structure of a chromosome and reintroduces alleles that have been deleted during crossover (Hosage and Goodchild, 1986). Mutation serves as a policy to prevent solutions from being trapped in local optima and is considered as a secondary mechanism in the operation of genetic algorithms (Jaramillo, Bhadury, and Batta, 2002). Generally, the positions to be mutated are randomly selected where each position has a small probability of selection, and replacing the values in the identified position with a contrary bit value forms a new structure. In Figure 8.3, the string is mutated by flipping the bit at position four from 1 to 0.

At the end of the breeding stage, each highest paid agent retains their finite state string strategy from step *t*, but has an agent attribute set as the genetically altered action strategy that they will distribute throughout the environment during the process of social mimicry. In the instances where the neighborhood of an unsatisfied agent has no successful agents, the agent either retains his own action strategy or adopts the strategy of the neighbor with the highest payoff.

8.3 The Model Environment

A central feature of the model is the ability of the user to set the model parameters that characterize a simulation scenario. Note on the left side of Figure 8.4 that the user can set the number of interaction cycles, minimum tolerance level, offer and distance costs, the percentage of successful agents to utilize in the evolutionary process, and the amount of the non-employment payoff. The Prisoner's Dilemma

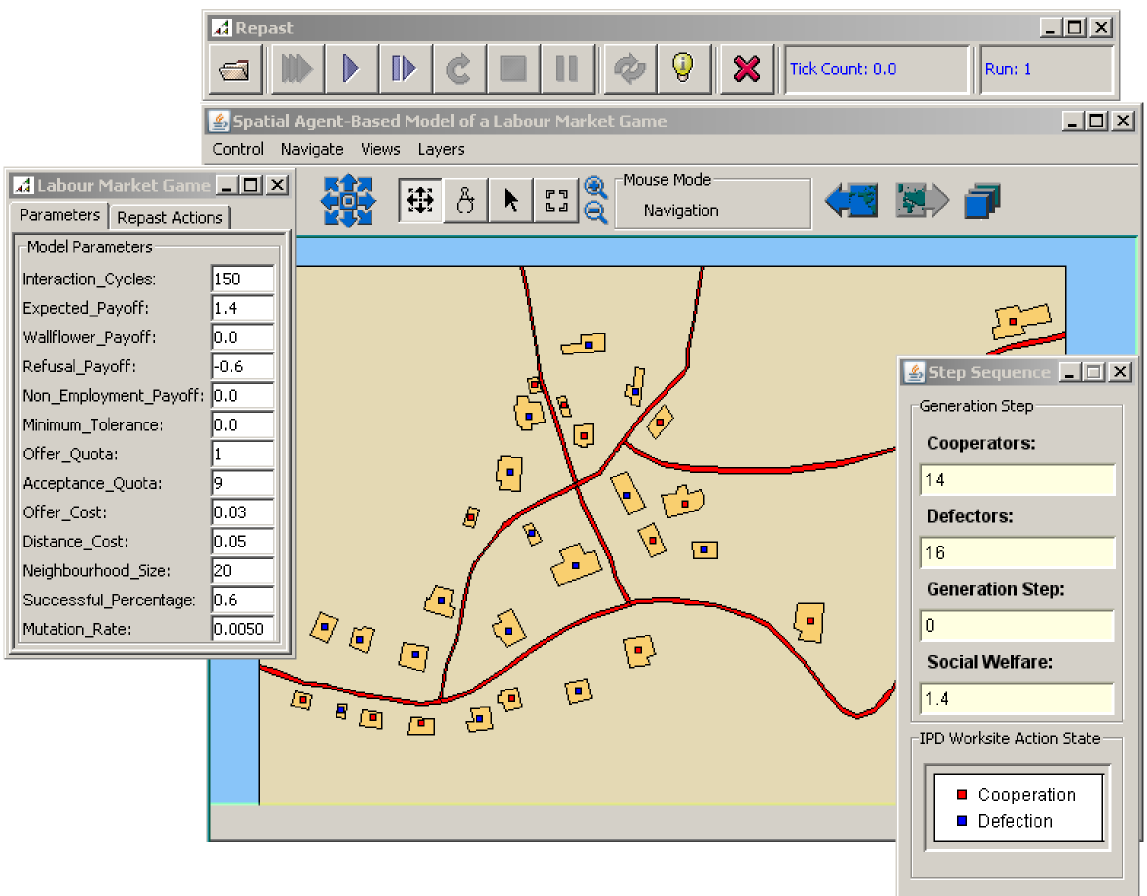

Figure 8.4: Interface of the Model of the Spatial Labour Market Game

payoffs (see Table 8.1) and the genetic algorithm conditions (e.g. mutation rate = 0.005) are set as the same as those presented in the original model of Tesfatsion (1997).

The spatial structure contains all of the necessary features in the study area for the simulations runs. Figure 8.5 displays the spatial environment consisting of non-fixed mobile employee agents and fixed non-mobile building agents in a synthetic labour market. The environment is an unbalanced labour market consisting of employees and firms that are linked by a road network. Locations of both types of agents follow a vector GIS geo-referencing convention. The building agents are polygons and the human agents are vector points, both imported into the GIS as ESRI© shapefiles. The relationship between both types of entities is hierarchical such

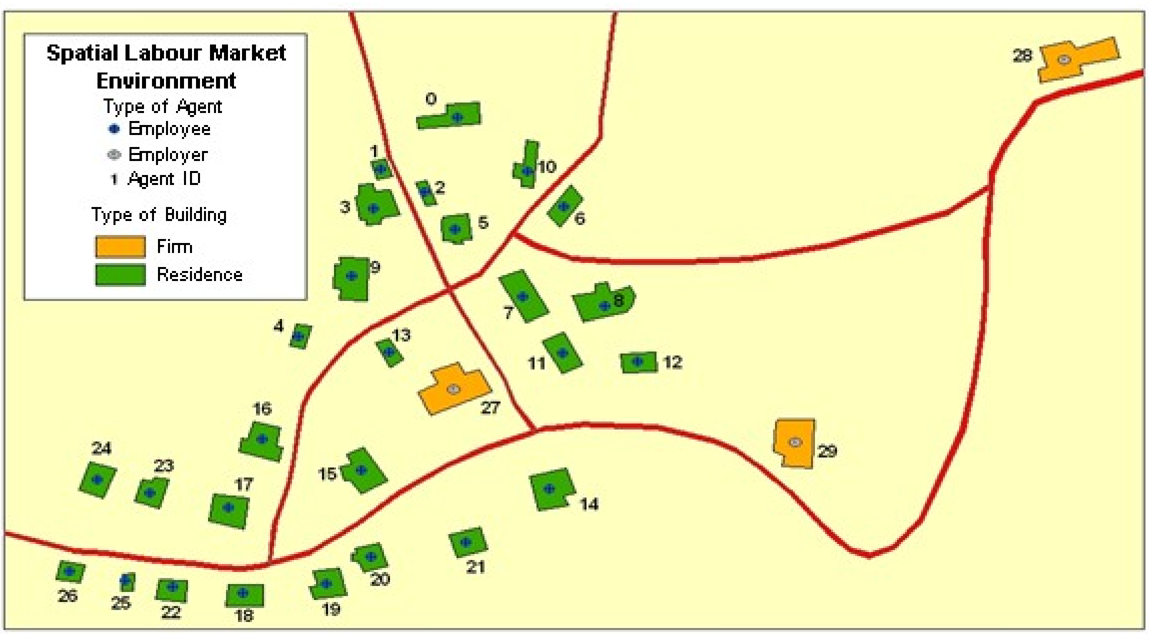

Figure 8.5: Artificial Labour Market comprising Mobile Agents and Fixed Building Agents

that each human agent is spatially nested within boundaries of a specific building agents. As an employee moves, the destination location is geo-referenced by pointing to a specific building object.

8.4 Simulation Experiments

The simulation experiments are based on a two-sided spatial labour market consisting of 27 employees and 3 firms, with this 9:1 ratio arbitrarily set to investigate the dynamics of a heavily unbalanced market environment. Each firm (agents 27 to 29) has the same acceptance quota of nine, and all of the employees (agents 1 to 27) have a similar work offer quota of one. These experiments investigate the influence of distance between employees and firms on the emergence of preferential partnerships, labour market participation rates, and worksite choices. Therefore, the three firms are intentionally located at varying distances from the residential concentration of employees, with firm agent 28 being the most distant. The initialization settings displayed in the model parameters panel in Figure 8.4 are unchanged for the simulation runs, except for the non-employment payment and distance cost. For the combinations of low, medium, and high non-employment payments and low and high distance costs (see Table 8.2), six spatial labour markets were generated and analyzed.

Table 8.2: Spatial Labour Market Model Initialization and Conceptual Validation Settings

Setting Level	Non-Employment Payment	Distance Cost	Spatial Adjusted Social Welfare
Low	0	0.05	1.35
Medium	0.565	N/A	1.3
High	1.05	0.15	1.25

For each labour market combination, a simulation run with 150 time steps was run 100 times. For each time step, there were 1000 generations of labour market game play and genetic evolution and social mimicry of action strategies within each firm neighbourhood. The structure of the simulation scenarios follows the research of Tesfatsion (1997) and Pingle and Tesfatsion (2001) with an analysis sequence of sampling the time steps at generations 12, 50 and 1000. The conceptual verification of the model is first evaluated by comparing sets of simulation results to the previous TNG findings (Pingle and Tesfatsion, 2001) for social welfare, preferential partnerships, and non-employment payment. A fully cooperative labour market would consist of agents with ALLC (always cooperate) action strategies, resulting in individual utility levels and a social welfare measure equal to the C payoff. Prior research demonstrates how the preferential partnership matching evolved the utility levels of the agents to the mutual cooperation level thus producing a labour market approximating a fully cooperative environment. Subsequent experiments altered the size of the offer and acceptance quotas and introducing employment parameters to compare the emergent labour markets to the utopian cooperative market. Pingle and Tesfatsion (2001) found that an increase in non-employment payment lead to greater instances of wallflower participants and higher unemployment and vacancy rates, but the pairs of agents that manage to match have a propensity to cooperate. However, the level of social welfare can decrease as the non-participation rate increases despite the proclivity of cooperation among matched partners. These conditions should also be prevalent in this model but have a geographic association.

For simulation runs with low non-employment payment (NEP) and low distance costs, the spatial labour market game is similar to the standard model of Pingle and Tesfatsion (2001). For simulations with a low distance cost, it is likely that the geographic effect on the matching dynamics of the agents will be minimal, because the spatially adjusted expected payoffs for the employees will still be considerably higher than the non-employment and wallflower payoffs. Figure 8.6 displays the latched pairings between the employees and firms shown as maps of flowlines for the three sampled generations. A latched pairing is a form of preferential partnership matching where an employee and firm continually decide to socially interact with each other for a set time frame due to the emergent level of trust and history of altruistic conditions between them. A flowline represents a preferential matching between an employee and a firm and each colored segment of the flowline indicates the total percentage of pairwise action choice for the 1000 generations that are averaged for the 150 labour market time steps. Visual inspection of the maps shows an almost equal percentage (approximately 25%) for each pairwise employee-firm action choice. This is quantified by the summary statistics in Table 8.3 that lists the total percentages for the employee-firm action choices for the three sampled generations for each labour market environment. It is likely that the random generation of finite state machines played a role in these simulation results, because each machine could follow a nice, greedy, or neutral action strategy. A network comprised of agents who are genetically predisposed to cooperation and shirker agents inclined towards defection would be less likely to experience a single dominant action choice pairing as compared to an amalgam of pairwise action choices

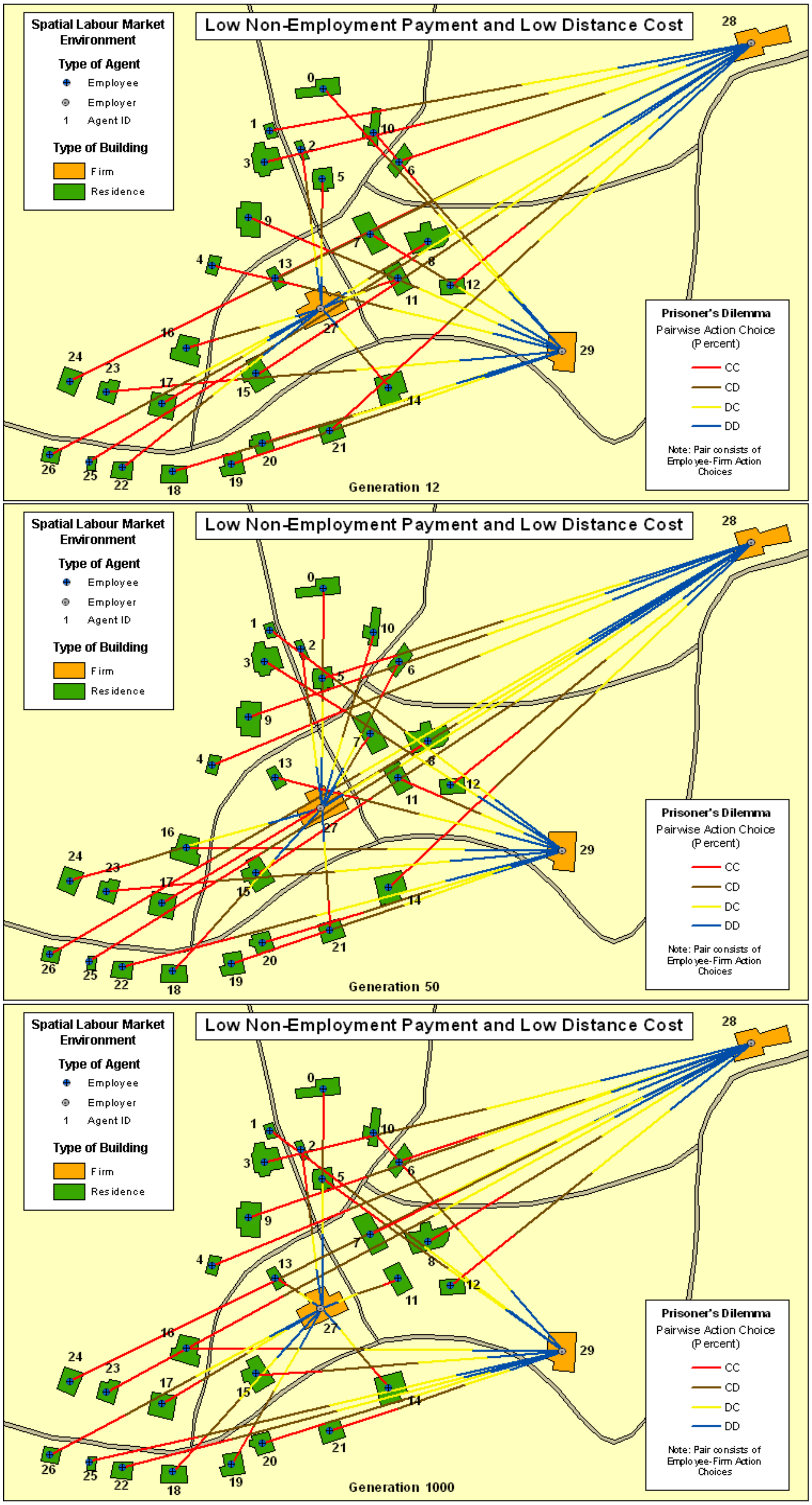

Figure 8.6: Simulation Results for Low NEP and Low Distance Cost

as evidenced in Figure 8.6. It is speculated that as *dc* increases there should be more instances of latching between employees and their spatially closest firm. However, with a low dc, this matching phenomenon does not occur as each firm is latched to employees that reside throughout the environment.

Table 8.3: Simulation Mean Values for Varied Non-Employment Payment and Distance Costs

Simulation State	Low NEP-Low DC	Medium NEP-Low DC	High NEP-Low DC	Low NEP-High DC	Medium NEP-High DC	High NEP-High DC
Generation 12						
Social Welfare	1.381	1.142	1.099	1.197	1.127	1.061
%CC	25.09%	25.80%	26.57%	25.54%	26.30%	26.81%
%CD	25.80%	24.42%	25.59%	26.34%	24.32%	24.61%
%DC	25.11%	25.33%	23.89%	24.54%	24.82%	23.92%
%DD	24.00%	24.45%	23.95%	23.58%	24.56%	24.66%
Non-Participation Rate	0.00%	7.40%	14.80%	0.00%	7.40%	18.50%
Generation 50						
Social Welfare	1.383	1.158	1.126	1.203	1.143	1.018
%CC	25.70%	25.45%	26.56%	24.46%	26.25%	26.84%
%CD	24.20%	24.45%	25.17%	25.22%	24.82%	24.72%
%DC	24.60%	24.18%	24.98%	24.43%	24.55%	22.75%
%DD	25.50%	25.92%	23.29%	25.89%	24.38%	25.69%
Non-Participation Rate	0.00%	3.70%	14.80%	3.70%	7.40%	18.50%
Generation 1000						
Social Welfare	1.387	1.174	1.129	1.185	1.136	1.027
%CC	24.40%	25.54%	26.40%	24.87%	26.19%	26.43%
%CD	25.90%	25.54%	24.52%	25.26%	24.23%	23.27%
%DC	25.30%	25.94%	24.52%	24.95%	24.08%	25.07%
%DD	24.40%	22.98%	24.56%	24.92%	25.50%	25.23%
Non-Participation Rate	0.00%	3.70%	14.80%	3.70%	7.40%	22.20%

An analysis of the agent worksite histories reveals that the persistent relationship between the latched partners is mutual intermittent defection (M-IntD), where the action choice of the agents alternates between cooperation and defection. However, instances of cooperative choices, both mutually and individually, increase as the action strategies that produce high payoffs are diffused throughout the environment. This is evident by the slight increase in the social welfare value for each successive generation for this simulation state. Note that the social welfare values are lower than the payoff for mutual cooperation payoff of 1.4. Tesfatsion (1998) presents scenarios where transaction costs and inactivity penalties lead to lower social welfare scores, and this is the case with the distance costs. For an unbalanced labour market where the utility levels of 90% of the agents can be decreased by distance costs, a lower social welfare value is anticipated. Thus, a spatially adjusted social welfare measure (see Table 8.2) is a more appropriate indicator of cooperative behavior in these simulations. This is defined as

$$\text{SpSW} = (\text{CC} - \text{I}dc) \tag{8.5}$$

,where CC is the mutual cooperation payoff and I*dc* is the initialization setting for distance cost. With SpSW values ranging from 1.346 to 1.351 for the sampled generations, a low NEP-Low *dc* labour market evolves towards a cooperative social interaction environment. This supports the findings of previous research about the importance of preferential partner selection and the evolution of action behaviors on the formation of an altruistic labour market network. A further interesting feature of the results is a labour market non-participation rate of 0% for the sampled generations, which represents the absence of wallflower agents. It is probable that the initialized settings for the minimum tolerance, offer quota, and acceptance quota influenced this behavioral pattern, but the consequences of these parameters will be constant for the subsequent simulation runs.

The next two sets of simulation runs investigated the labour market dynamics from an increased NEP with a low distance cost. As the NEP is raised, employees and firms are increasingly enticed to leave the labour market as they evaluate how the expected payoffs will be adjusted for penalty costs. Even with a low distance cost, it is possible that a spatial clustering of non-participant employees will emerge. Figure 8.7 displays the results of the simulations with a medium NEP value and a low distance cost. Three discernible patterns are evident on the maps for each sampled

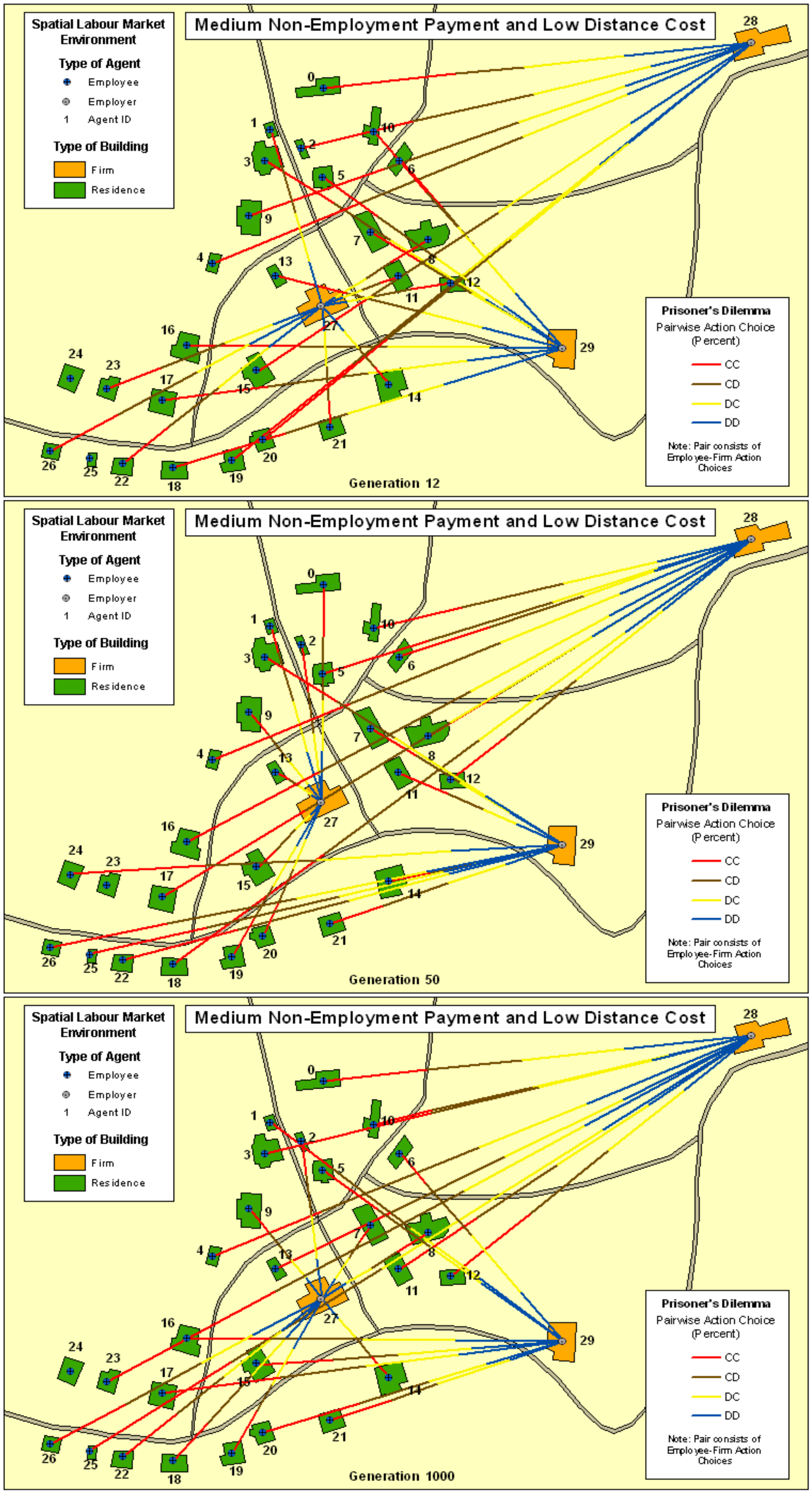

Figure 8.7: Simulation Results for Medium NEP and Low Distance Cost

generation. Firstly, the flowlines between the latched employees and firms have approximately equal percentages, as shown in Table 8.3. Secondly, each of the firms is latched to employees who live throughout the environment so the distance cost only becomes a consideration for the employees when they make multiple movements throughout the environment as they submit work offers. Lastly, instances of non-participation in each of the market generations are represented as isolated employees lacking a flowline to a firm, but these disconnected agents only comprise a small proportion (7.4%) of the total population. This increase in unemployment has also led to the expected decrease in social welfare to a level of 1.142.

The maps in Figure 8.8 present the simulation results of a high NEP and low distance cost, which have a similar spatial pattern to those in Figure 8.7. The flowlines to each firm originate from employee locations throughout the environment, and it appears that the percentages of action-choice pairings are visually unchanged. Table 8.3 indicates that the percentage of CC action-choice pairing has increased albeit by a small amount. This increase in cooperative behavior is negated by the influence of a high NEP payoff as more employees decide not to participate in the labour market. In addition, social welfare tends to decrease to a level of approximating the unemployment payment as the NEP is increased. Figure 8.8 shows that the unemployed agents tend to be spatially dispersed when distance cost is low, and the employment status of some individuals can vary at each sampled generation. Thus, the decision of an individual to leave a labour market is swayed more by the temptation of the non-employment compared to the expected payoffs and less by the distances to the firms.

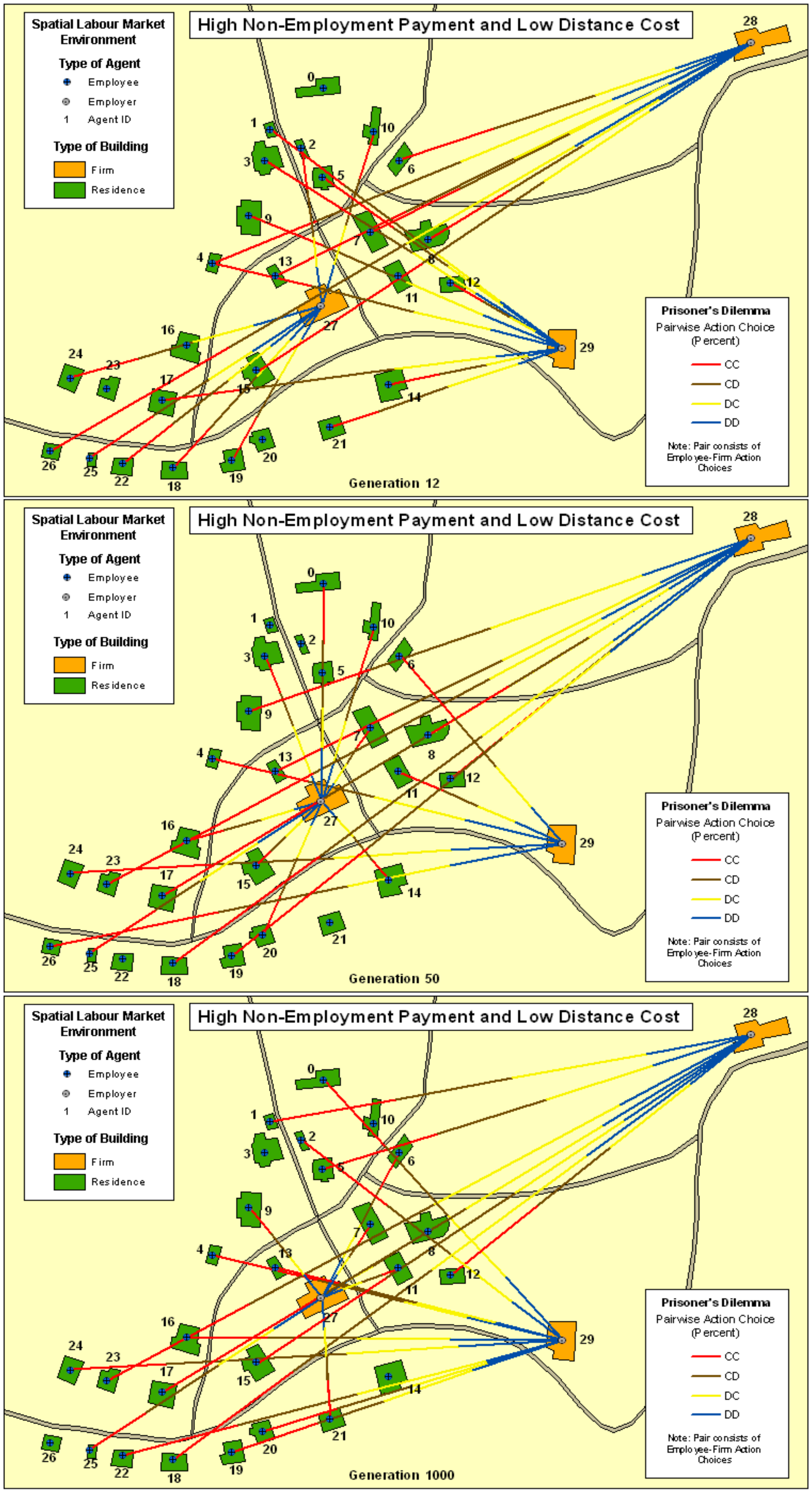

Figure 8.8: Simulation Results for High NEP and Low Distance Cost

The influence of place on the emergence of cooperation and the dynamics of a labour market can be examined by increasing the distance cost in the simulation scenarios. With high *dc* simulation runs, the interrelationship between NEP and distance costs and their influence on the emergent structure of a labour market is revealed more clearly. In Figure 8.9, the low NEP is an incentive for all agents to participate in the labour market, but instances of non-participation occur at generation 50 and 1000. An agent becomes a non-participant when the distance costs, offer costs, and refusal payoffs are less than or equal to the non-employment payment. The simulation time step processes for these non-participant agents consists of the movement to and submission of a work offer to at least two of the firms as well as a mobility event to return to the place of residence. Recall that the acceptance quota of the firms for these simulations is nine so there are vacancies that these employees could fill. However, the potential of a third work offer rejection with the associated refusal penalty and distance cost influences these employees to leave the labour market. This finding suggests the possibility of employees engaging in fewer movements and work offer submissions to the detriment of the firms. There is also the likelihood that firms that are spatially closer to the employees may have a slight advantage in procuring preferential partnerships over their more distant employer counterparts. The flowlines of the maps in Figure 8.9 for generations 50 and 1000 show that firm 27 has M-IntD latched relationships with nine employees, but firms 28 and 29 have only eight preferential pairings for generations 50 and 1000. The percentages of action-choice pairings shown in the flowlines visually mimic those of the other low NEP simulations, but the influence of a higher *dc* in a low NEP

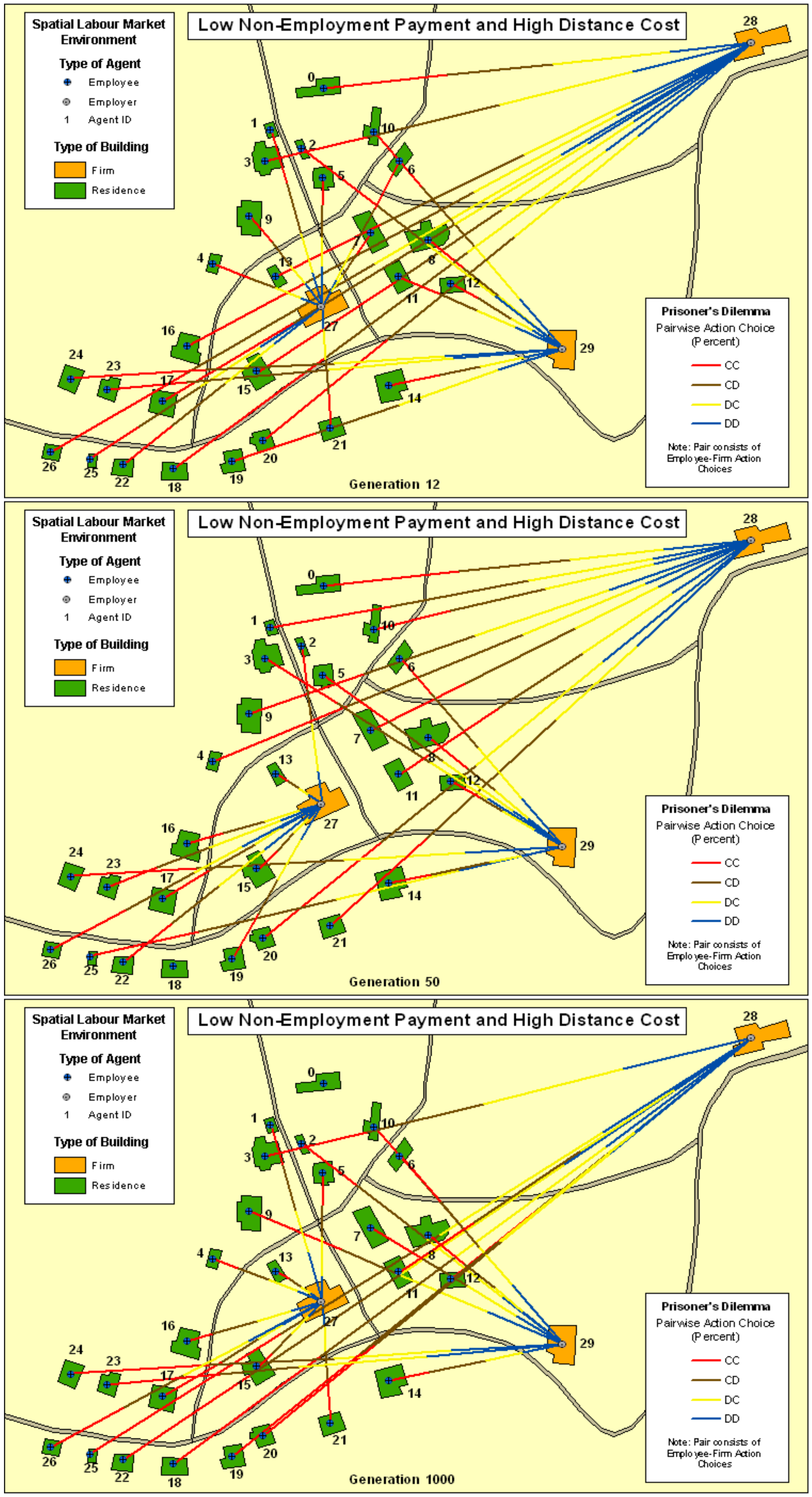

Figure 8.9: Simulation Results for Low NEP and High Distance Cost

simulation setting can be evaluated by comparing the social welfare values against the thresholds listed in Table 8.2. The social welfare value for each of the generations for low *dc* is above the threshold, but less than the threshold for high *dc*. As an average utility level, social welfare in a low NEP-high *dc* simulation depends on the adjustments of each agent's utility level for all movement events and the presence of non-participating individuals

Visual inspection of the simulation results in Figure 8.10 shows an anticipated increase in the number of non-participant agents in all sampled generations as the non-employment is increased from low to medium, and a pattern of spatial clustering of unemployed agents in the southwestern section of the environment for generations 12 and 50. Also, there is an increase in the CC action-choice pairings of approximately 2% over the low NEP-high *dc* values, but the altruistic nature of the environment, as seen by the lower social welfare value, is weakened by the increased number of non-participant agents.

A simulation with a high NEP and high *dc* will model an emergent labour market structure comprising a considerable number of non-participants within the agent population, some having left the market due to their road distance from the firms (Figure 8.11). With the highest non-participation rates, 18.5% to 22.2%, the maps for the high NEP-high *dc* simulations display both a spatial clustering of unemployed agents and individual instances of non-participation throughout the environment. Specifically, the non-participants are becoming clustered in the southwestern section of the environment. The noted pattern is the self-organization of the preferential partnerships flowlines into localized networks of M-IntD latched

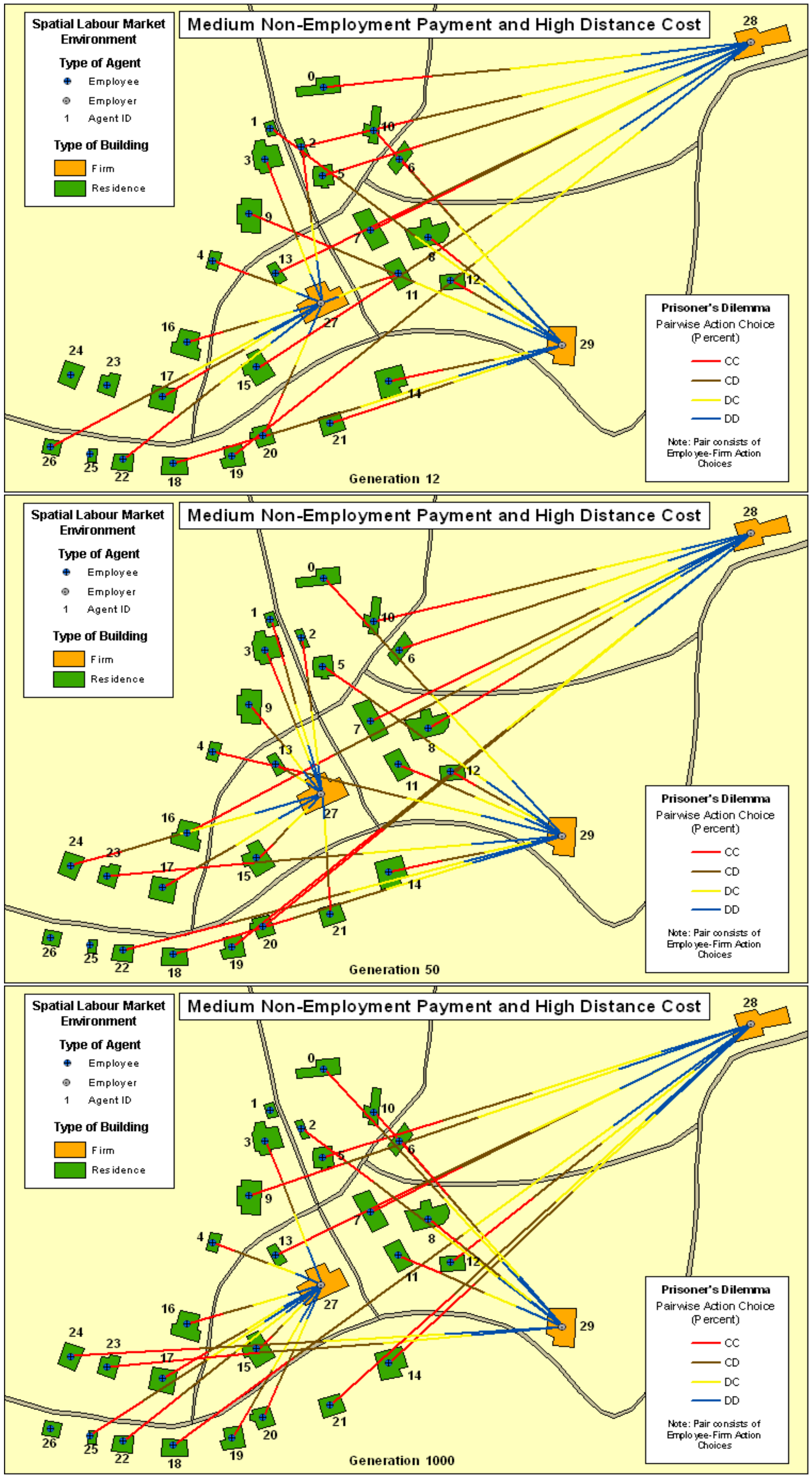

Figure 8.10: Simulation Results for Medium NEP and High Distance Cost

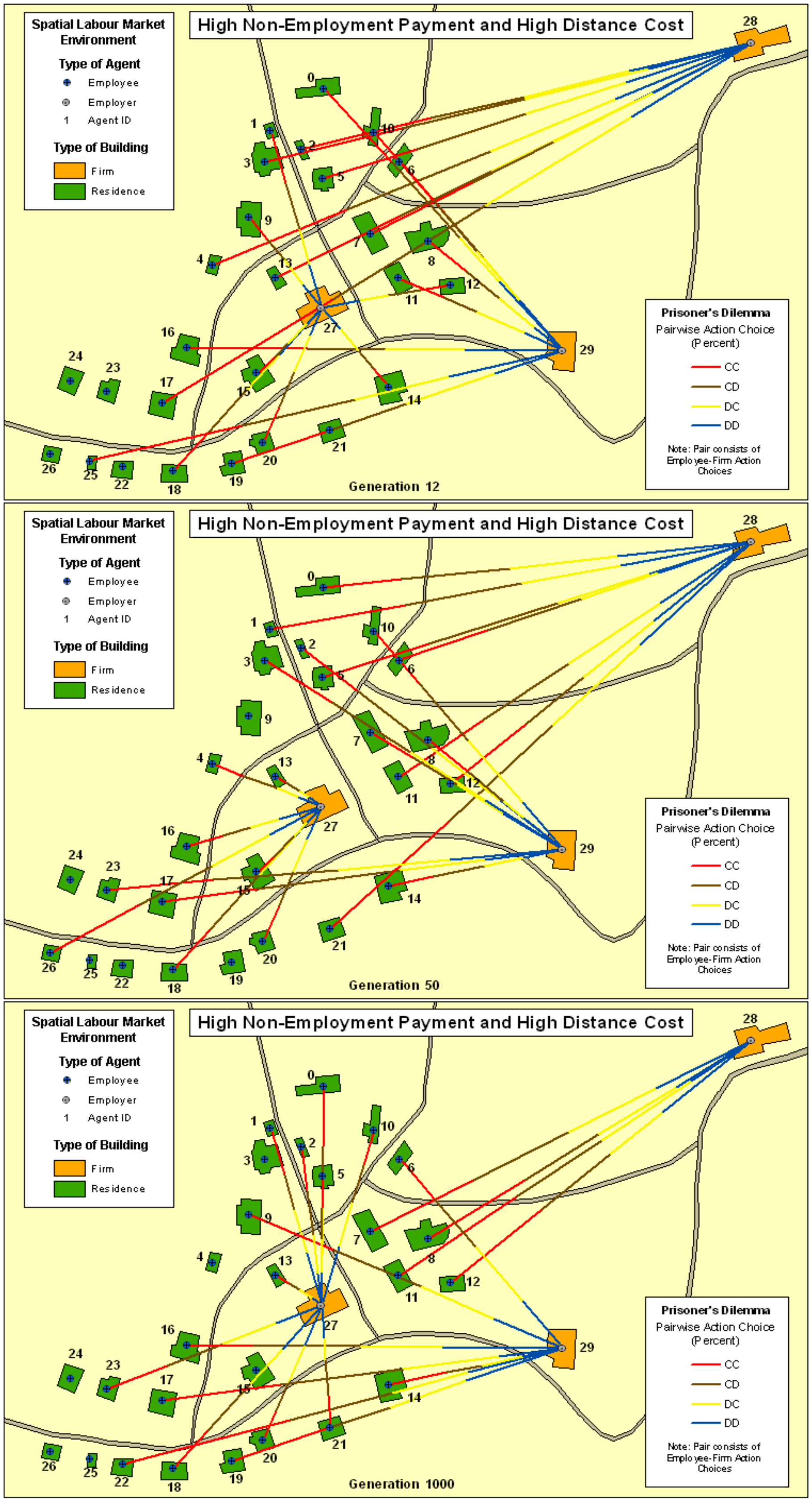

Figure 8.11: Simulation Results for High NEP and High Distance Cost

firms to geographically closer employees, which is especially evident for firm 28 at generation 1000. At generation 12, firm 28 has latched relationships to seven employees located throughout the environment, but there are only preferential partnerships to the four closest employees at generation 1000. The implication of this process is the possibility of a reduction of the available employee pool for the more distant firms, which puts them at a competitive disadvantage with the other employers. Tesfatsion (1998) states that the firms with high vacancy rates often resort to unprovoked defection when they receive a work offer in an attempt to procure a payoff higher than the wallflower payoff. There is also the situation where the non-employment payment and distance cost values are set so high that a distant firm receives no work offers and is consistently assigned the wallflower payoff. These circumstances could deter the emergence of mutually cooperative behaviour between agents resulting in a lowered social welfare state. The vacancy rates for firm 27, 29, and 28 at generation 1000 are 0%, 22.2%, and 55.5%, respectively, and this is partly due to their location within the modeling environment. Even though firms 28 and 29 have significant vacancy rates, the percentage of CC action-choice pairings from generation 50 to generation 1000 only slightly decreased for firm 28. This fact combined with increases in employee non-participation may explain why the social welfare values are the lowest for these simulations, ranging from 1.018 to 1.061.

A detail that needs to be considered is the diffusion of the evolutionary action strategies in a high NEP-high *dc* environment. The successful agents are those who actively engage in the employment process and receive the highest payoff during a round of game play. As such, the diffusion of action strategies of the successful agents to the unsatisfied individuals is meant to supplement and direct the behavorial processes of all participants in the labour market. The issue for a high NEP-high *dc* simulation event is that the highest paid agents could be those who have chosen the non-employment payment. Non-participation is theoretically suboptimal in a labour market model, so the preservation and imitation of less successful action strategies could slow the evolution of the system towards a cooperative state. This is a topic that will be thoroughly investigated in future versions of the model.

8.5 Conclusion

This paper presents a spatial agent-based model of an evolutionary labour market game developed to simulate employee-firm relationality within a synthetic geographic environment. Built on the original methodology of Tesfatsion (1997), this model expands the preferential partnership mechanism to consider agent mobility behaviors in the matching process, and supplements the social mimicry component with a geographically constrained diffusion of successful action strategies that are evolved with a standard genetic algorithm. The goal of the system is to simulate the emergence of cooperation within a market environment from the mobility and socialization decisions of the agents as they engage in cycles of labour market interactions.

Six sets of simulations results document the effect of varied non-employment payments and distance costs on the emergent patterns of employment and cooperation within the model. For a low NEP-low *dc* simulation, distance played a minimal role in the dynamics of the labour market, but the results support the findings of previous research of the value of preferential partnership matching in the evolution towards a fully cooperative market environment. As the non-employment payment is raised from low to high, increased instances of non-participation were spatially dispersed throughout the labour market. The localized instances of paired agents engaging in CC action choice behaviours will increase at the higher NEP settings, but the environment-wide level of cooperation, measured as spatially adjusted social welfare, will decrease due to the lower utility levels assigned to the non-participant individuals. As *dc* was set at the high thresholds, the cumulative distance penalty had a stronger negative influence on the employee decisions to participate in the labour market. The significance of place in the labour market game is highlighted with the results from the setting of high NEP-high *dc*. The spatial clustering of unemployed agents occurred within a small number of time steps, but a noticeable emergent pattern is the localization of the latched partnership network between employees and the more distant firms. The network of firm-employee relationships reorganized into a smaller group of the most distant firms latched to the geographically closest employees.

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9.0 Paper 4: A Conceptual Framework for a Spatial Agent-Based Model of Self-Organizing Leadership and Cooperation.

Abstract

This paper presents a conceptual framework to formalize an agent-based model of emergent leadership and cooperation in a socio-geographic environment. Self-organization of the configuration of social networks and the spatial topology of interaction neighbourhoods is central to the proposed framework. A review of the theory of emergent leadership is provided to derive and support the basic postulates for the model. The modeling aspects then detail the integration of social and spatial components to simulate the non-linear interactions that occur within the "space between individuals". The primary social component is an N-Person Prisoner's Dilemma mechanism that simulates emergent cooperation and social identity from the consensus behaviors and actions of citizens in interaction networks. The spatial aspects simulate the geographic reconfiguration of neighbourhoods from the mobility dynamics of agents as they search out partners relative to expected payoffs. Leadership emerges in the environment from the tensions in the decision choices of agents during social exchanges and the enabling actions of administrative and cooperation leaders. The mobility choices of unsatisfied agents are contingent on the possibility of a positive payoff from interactions with identified leaders, where followers purposely move to the locations of these influential cooperators. At the end of each social exchange, action strategy mimicry is implemented with the unsatisfied citizens imitating the strategy of the neighbours with the highest payoffs. The conclusion is a discussion of potential "what-if" scenarios to gauge the merit of a formal model.

9.1 Introduction

The study of leadership has been an important topic of social science research for decades, but has been criticized due to the proliferation of theories with no universally accepted framework for understanding the dynamics of leadership (Bass, Avolio, and Goodheim, 1987; Yukl, 1989). In a simple context, leadership has been described as the process of social influence in which one person can enlist the aid and support of others in the accomplishment of a common task (Chemers, 1997). The leadership literature presents a myriad of theories that associate social influence with the characteristics of leaders and the situational factors that guide the communication and interactions between leaders and followers. Traits theorists (Jenkins, 1947; Gibb, 1947; Kilpatrick and Locke, 1991) believe that certain physical, social, and personality traits distinguish leaders from non-leaders in social settings. Judge and Bono (2000) present a dispositional framework that links the five-factor model of personality to leadership behaviour. They determined that leadership effectiveness could be estimated by the degree of extroversion, agreeableness, and openness of the individuals. Behavioural theorists (Bales, 1954; Mann, 1965) focus on the behavioral dimensions and actions of the leaders as they bring about change. With this approach, the assumption is that effective leaders can be identified from the right combination of approach and people orientation (Fleishman and Harris, 1962). In the 1960s and 1970s, research turned to contingency theories to account for situational factors that influence effectiveness from the style of leadership exhibited by individuals (House and Mitchell, 1974; Fiedler, 1976). Leadership style generally falls into two categories: transformational and transactional. A transformational leader influences followers to work for collective goals, and the level of trust and respect that they have for the leader motivates them to go beyond what is normally expected of them (Bass, 1985). Transactional leadership is predicated on the motivational abilities of leaders to clarify how follower needs can be fulfilled in return for their efforts at satisfying their job requirements.

These traditional theories are deterministic top-down approaches that assume equilibrium end states. Contemporary leadership researchers (Lichtenstein et al. 2006; Hazy, 2007; Plowman et al. 2007; Uhl-Bien et al. 2007) have stated that these conventional methods are inappropriate and out of date to handle the leadership dynamics in the modern knowledge work environment. They have proposed alternative frameworks drawing from aggregate complexity theory (Manson, 2001) that consider leadership to be an emergent property from the nonlinear interactions among groupings of leaders and followers. The theory of emergent leadership focuses on evolving social networks of informally interacting agents, where the leader enables rather than aligns the networks (Uhl-Bien et al. 2007). Instead of controlling the interactions between individuals for desirable results, leaders are adaptive when they encourage and nurture conflicting ideas and options within the social unit. A theoretical principle of leadership in a complex system is the emergence of localized leader-follower groupings that achieve order, because their path-dependent social interactions produce unexpected outcomes (Chiles et al. 2004). The stochastic dynamics of the informal interactive interdependency between the individuals leads to bottom-up behaviors that collectively lead to the emergence of structural changes in the social network.

Uhl-Bien et al. (2007) state that the basic unit of analysis in the formal models of self-organizing leadership is the complex adaptive system, a dynamic network of interacting, interdependent agents who are bonded in a cooperative dynamic by a common goal, outlook, etc. Of interest to this paper is the research utilizing agent based modeling (Hubler and Pines, 1994; Carley and Ren, 2001; Black et al. 2006; Dionne et al. 2010) as the complex adaptive systems to simulate the emergence of leadership at the micro-leadership level (individuals in social groups). Agent-based models are ideally suited for simulating leadership in social networks, because the individual decisions and behaviors of each agent generate system-wide emergent capabilities and adaptability in leader-follower exchanges. The efficacy of the leadership within a multi-agent environment will depend on the level of cooperation between the agents, and their ability to receive advice and knowledge from other individuals. This leads to the formation of cooperative aggregates of agents that follow an influential leader in making their individual decisions (Anghel et al. 2004). There has been leadership literature that looks at the motivational influence of the leader to encourage cooperation among the agents (Solow et al. 2005), but there are few studies that consider the cooperation dynamics of the agents as it relates to their personal benefit and leadership position in the social environment.

Cooperation is behavior that may initially cost a person or group but ultimately benefits other individuals or social aggregates. While this may seem an uncomplicated concept, the derivation of satisfactory theoretical explanations for real-world altruistic behavior has been a challenge (Killingback and Doebeli, 2002). However, the Prisoner's Dilemma has become one of the most widely adopted methodologies for studying the evolution of cooperation in simulated social environments. The Iterative Prisoner's Dilemma is the common approach of simulating emergent cooperation in pairings of continually interacting agents, where cooperative and non-cooperative behaviors are reciprocated conditioned on the emergent level of trust between the partners. Leadership in the Iterative Prisoner's Dilemma game has been shown to be an important process in achieving a steady state of cooperation in social networks (Zimmerman and Equiluz, 2005). As dyads of agents interact, followers will adopt the strategies of the neighbouring cooperative individuals with the highest aggregate payoffs, setting these agents as the cooperation (C) leaders in the social environment. The emergence of global cooperative steady states was found to depend exclusively on the survival of certain C-leaders with the maximum payoffs in the network, because these were the individuals that unsatisfied agents would gravitate towards as they searched for partners for future game play episodes. However, the general assumption is that agents only interact with a single matched partner during each round of game play, and this simplifies the network concept of neighbourhood. Social networks, such as a city or large corporation, are often comprised of simultaneous interacting agents in a multitude of social configurations (pairings of agents, small localized groupings, or the entire community). There has been an increase in the research and application of the N-Person's Prisoner's Dilemma (NPPD) to investigate the emergence of collective cooperation in social groupings. Referred to as a social dilemma situation, a player has to choose between his own interests or exhibit cooperative behaviors that benefit the grouping of N players. Simulations have shown that agents meeting repeatedly develop a propensity to cooperate and exhibit altruistic behaviors, and this cooperation is sustained by the reciprocity of neighbours within the social environment. Several authors have also elaborated on the delineation of NPPD neighbourhoods by investigating the spatial dynamics of social networks. Akimov and Soutchanski (1994) developed a spatial NPPD game to relate how collective cooperation depends on the behavioral patterns of simple automata within a cellular automaton. Szilagyi (2003) presented a cellular automata model of NPPD based on the interactions of irrational agents in a social unit and revealed how the chaos like actions of the agents was an important condition for decentralized group cooperation. Power (2009) presented a spatial agent-based model of NPPD that simulated the emergence of cooperation from the behaviors of mobile citizen agent in a real world socio-geographic community. A practical extension of the spatial NPPD models is to provide a conceptual abstraction that simulates the emergence of leadership from the mobility influenced altruistic decisions of agents.

The purpose of this paper is to propose a framework for a spatial agent-based model that simulates self-organizing leadership from the structure of cooperation and trust that emerges from multi-agent social interactions. The theoretical concepts of the model are presented as separate but interrelated methods that simulate the spatial variability in the social interactions that define leadership structure with attention given to the assumptions and computation approaches. From these assumptions, the basic elements of the model are established and the integration between them considered. The paper is organized as follows. In section 9.2, the theoretical principles and implementations of self-organizing leadership in organizational sciences and community development practices are reviewed to derive the basic precepts for the conceptual model. Section 9.3 focuses on the components required for the morphology of a spatial NPPD agent-based model of emergent leadership. Section 9.4 presents the formal design of the integrated components of the simulation model based on the supposition that cooperative decisions of mobile agents can lead to the emergence of C-leaders within a social network. Cooperation is established and sustained according to the social preferences of the agents in selecting neighbours for game play. C-leaders are agents who prefer continued altruism and will accept a payoff lower than the largest possible utility level of defection. Followers are unsatisfied agents who search for and choose new partners relative to expected payoff, which triggers a reconfiguration of the topological structure of the spatial and social network. The mobility decisions of the defection (D) leaders also alter the network structure as they seek out cooperative neighbours to exploit. From memories of past payoffs, a level of trust develops between the followers and the C-leaders, and this increases the probability of the unsatisfied individuals moving to the location of the C-leader. In a contrary manner, known D-leaders are avoided by exploited followers so these defectors to have to perpetually invade neighbourhoods of unsuspecting cooperators. Each simulation time step will conclude with social mimicry, where the unsatisfied followers adopt the action strategy of the neighbour with the highest payoff. The discussion section details the conditions for the development and application of the proposed model, and discusses potential “what if” scenarios for simulating cooperation and leadership in socio-geographic environments. The paper concludes with a summary of the processes in a model to simulate the dynamics of leadership in a well-connected community.

9.2 Theory of Self-Organizing Leadership

The concept of emergent leadership is founded on the principles of aggregate complexity theory, specifically the dynamics that explain the self-organization of social networks. Lichtenstein et al. (2006) describe leadership as an outcome of the tensions in the relational interactions among agents within a social network. This tension causes a network to emerge out of states of disequilibrium when it is at the "edge of chaos" (Gilchrist, 2000; Kuhn, 2009). This is when the system is most open to new input and will permit novel information and options to enter the interaction network and challenge the status quo. Conflict is often a necessary condition for the early stages of emergent leadership, both amongst the individuals and between the entire social network and outside contacts. It is this state of disequilibrium that will cause agents to communicate with one another and to interact and explore options for localized actions within the network. The intensity and range of the interactions will change as information is shared and diffused throughout the network causing individuals to continually adapt and act differently from the feedback about the actions of others. However, Onyx and Leonard (2010) state that even though disequilibrium may be encouraged, social networks also have forces or "deep structures" that push the network towards equilibrium. Whether through a common set of principles or objectives, turbulence in the social interactions can be limited by the cooperative and consensus decision-making among the participant agents. These bottom-up interactions of the social agents lead to an emergent form of order which Heihetz et al. (2009) refers to as "controlled disequilibrium".

Uhl-Bien et al. (2007) present a complex adaptive system outline of emergent leadership that focuses on social positioning in evolutionary networks of informally interacting agents. They argue for a departure from the traditional view of a leader as an authoritative figure influencing and guiding the actions of followers to obtain an organizational objective. Instead, they view leadership involving interrelated roles for administrative, adaptive, and enabling leadership. Administrative leadership is the top-down coordinating actions and decisions of agents in formal managerial positions who plan activities to satisfy organizational outcomes. Adaptive leadership is the micro-level emergent, interactive dynamics among agents that produces collaborative change within a social network. Enabling leadership is intended to identify and manage the conditions required for adaptive leadership including any norms and institutional conditions introduced into the system by the administrative leader. The essence of self-organizing leadership is that leaders enable rather than dictate the network dynamics by encouraging and allowing individuals to remain engaged and connected despite the tensions within the social networks. Adaptive leaders enable behaviors that encourage conflict in the network to motivate and coordinate the interactions, and they direct attention to what is important and provide meaning to events. Unlike the standard approaches, leaders in a complex system frequently have little authority in the organization and can lead in a temporary capacity. The individuals who assume a role of a communicator become a *tag* within the social network (Holland 1995; Marion and Uhl-Bien 2001) when they are recognized as influential in coordinating initiatives and facilitating interactions amongst the individuals. A tag is a representative social standing or reputation associated with a leader from the role(s) he undertakes in catalyzing actions and directing behaviours in the social network. For example, a leader could be a tag for social empowerment due to his efforts to include disenfranchised citizens in the decision process that address civic issues. Another person could be tagged as an entrepreneur as his neighbours recognize and appreciate the leadership displayed in past business venture successes. With the condition that a tag is often unassociated with a position of formal management, there can be multiple leaders who share the facilitator role in tandem. The scope of the interactions is intended to bond the immediate social network as well as distinguish it from other external groups. Interactions within the group facilitate a social identity that incites individuals to accept and appreciate the opinions of others, while interactions with outside groups increase the importation of new ideas, information, and innovations from the environment.

Lichtenstein et al. (2006) view leadership as an emergent event from the nonlinear interactions that occur between the “spaces between individuals” in a social network. The bonding within a social network emerges from human interactions that depend on an orientation amongst the individuals (Bradbury and Lichtenstein, 2000). This relationality postulates that self-similarity is associated with organizational identity, because it occurs when an individual’s beliefs become self-defining (Schneider and Somers, 2006). Members in a social network develop a sense of belonging to the group when their self-identity approximates their perceived identity of the organization. As such, the structure of a social network consists of evolving connections and interdependencies between people rather than the selfish actions of individuals. Leadership is thus a system phenomenon reliant on communication and information diffusion within the bonded social space. The term space is important, because it suggests a means of analyzing adaptive leadership in terms of the social distance among the individuals in the network. Episodes of leadership can be identified by analyzing changes in the closeness in the social interactions resulting from an individual's actions to mobilize others to seize new opportunities and tackle relevant issues. This degree of closeness within the network will be both positively and negatively influenced by the tensions in the social interactions. Tensions can push people together to develop a consensus approach to a common concern, adopt a new innovation, or plan an agenda. However, tensions can also cause individuals to question their place in the social grouping when their self-identity increasingly differs from the organizational identity despite the efforts of a moderator. Emergent order within the environment can rely on the social and temporal strength of the connections between those individuals who feel closer to and those who are further alienated by the interactions in the social network.

The "space between individuals" has a geographic connotation that many scholars in organizational science have ignored or dismissed in their formulations. However, researchers in community development have studied emergent leadership as a non-linear process of interactions within a community, which has both social and spatial processes. A tenet of community development is that the success of an individual or a group's efforts to mobilize the community hinges on the interactions between citizens as they utilize social capital. Gilchrist (2000) presents a model of the well-connected community as an adaptive socio-geographic network of inter-locking relationships. She argues that community development practitioners need to support and shape social networks for the emergence of empowering forms of communal actions. Community leaders are the individuals who facilitate communication and cooperation within the network producing a strong collective identity based on shared geography or common interests. Onyx and Leonard (2010) reviewed five case studies to determine the common elements of self-organizing leadership that recur in successful community development programs. Community leaders are often tagged individuals, most with little formal authority, who have the vision and initiative to articulate a future vision of the community's social, cultural, and economic conditions. An important spatial pattern that often occurs is the movement of followers to locations within close physical proximity of the prominent citizens to both share and receive information. These spatial groupings were both the results of concerned or interested citizens convening for public meetings at a communal facility, such as a school or town hall, and the conscious decisions of people to search out and move to the locations of the leaders. It was determined that when leaders become embedded in the formal and informal networks within a community they inherit a level of trust and reverence amongst the followers. Theoretically, system order from the processes associated with emergent leadership in a socio-geographic environment is the product of the self-organization of both the social connectivity network and the spatial topology of the well-connected community.

9.3 Spatial Agent Based Model of NPPD Emergent Cooperation and Leadership

The abstract framework of the model is founded on the processes that define leadership in a socio-geographic community. From a research perspective, a socio-geographic community is both a geographical object and a sociological subject. It is an integrated geographic network of social individuals defined by the communication patterns and flows throughout an evolving area of collective social interactions. Flows refer to both random movements throughout the modeling environment and agent specific decisions to move to the location of influential agents. As a sociological subject, a community codifies behaviors to control the processes of social interactions. For self-organizing leadership, the community becomes a social system of individual agents engaging in both local communication and actions involving a self-identity, social identity, and collaborative efforts. Thus, the simulation of a socio-geographic community considers agents with individual characteristics and behaviours, the relationship among and between them and the environment, as well as how these characteristics and relationships change through time and space. The agent-based model must simulate the "space between individuals" in both a sociological and geographic sense.

9.3.1 Object Oriented Relationality: Agent States and Transition Rules

Bathhelt and Glûckler (2003) demonstrate that social relationality in geographic research emphasizes the importance of contextuality in human actions. For the computational development of spatial models of relationality, social individuals are geographically interconnected in communication and cooperative processes with their neighbours. The emergent localized processes will depend on the actions of the agents, who have to be represented as autonomous objects of knowledge and information.

Many of the spatial agent-based models in the literature have been developed with object oriented programming within a modeling platform such as Repast Simphony© or Netlogo©, and the same approach is proposed for this research. These models are computational representations of a complex adaptive system consisting of generative heuristic mechanisms to simulate multi-scalar interactions between entities. From a programming perspective, each agent is represented as an object that changes its state, location, and interactions with others according to transition rules at successive time-steps. Figure 9.1 displays an example of a modeling framework for a

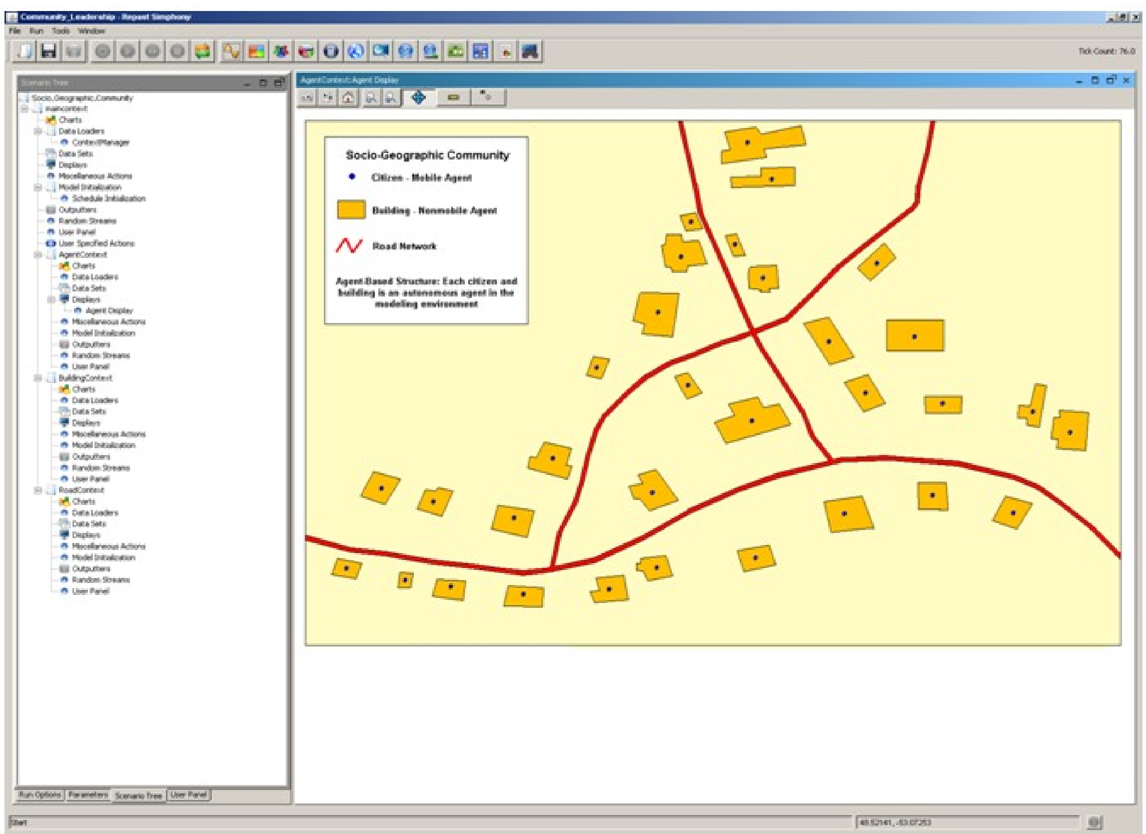

Figure 9.1: Repast Simphony Display of a Socio-Geographic Community

socio-geographic community developed with Repast Simphony©. This object-based view of a community consists of both fixed and mobile geographic automata, each ontology of object assigned specific state variables during initialization and a set of transition rules to determine how these states change over time. The citizens are mobile agents who actively engage in the social interactions associated with emergent leadership. Each citizen is assigned state variables that determine their social position in the network and spatial location in the modeling environment. Social position requires parameters that set the agent's participation in NPPD game play, specifically interaction strategy, last action choice (cooperation or defection), and payoff level. An agent's social position in the dynamics of leadership is tracked with variables that remember tags assigned to certain influential citizens, identities of any cooperation (C) and defection (D) leaders from time step t, and the level of self-identity in the social network. Spatial position is logged with pairs of geographic coordinates of the location of the citizen at time t, the t geographic coordinates of tags and C-leaders, the destination locality at time $t+1$, and an arraylist of the neighbouring citizens who will participate in episodes of NPPD play.

The buildings are non-mobile features and structures that are directly geo-referenced in the model as origins and destinations of the citizen agents. Each building has a single state variable that describes its occupancy type: household residence, community center, church, school, etc.

9.3.2 State Transition Rules

Simulation of the spatially enabled social interactive behaviors of citizens requires an integrated knowledge of system state, location, and neighbourhood rules.

State transition rules are only needed for citizen agents and consist of four sets of heuristics: (1) those relating to the probability of cooperative action, (2) rules that determine if an agent copies the strategy of neighbourhood leaders, (3) rules that update a citizen's social identity at time step *t*, and (4) rules that update the identification of tags, C-leaders, and D-leaders for each agent at time step *t*.

9.3.3 Movement Transition Rules

An object-oriented approach will coordinate movement as discrete event simulations with a scheduling mechanism directing the sequencing of agents' mobility behaviors. Movement rules manage both the travel of the citizens to randomly selected destinations and the agent specific decisions to commute to the locations of influential agents. Standard movement requires a set of rules that first randomly selects one of the buildings and relocates the citizen to the facility. Directed movement of citizens to the locations of tags and leaders is coordinated by rules that consider the degree of social space accorded to them by the citizen at *t*. Bounded rationality sets the condition that a citizen moves to the time *t* location of a selected tag even though that individual may have relocated at time step $t+1$. In the instance where there are numerous identities of multiple tags and leaders stored as agent states, one is randomly selected and the citizen moved to the building where the influential individual was situated at time step *t*. Mobility behavior is an important element in the spatial agent-based simulation of cooperation in a social environment, because it sets the neighbourhood configuration for the NPPD game play.

9.3.4 Social Interaction Neighbourhoods

A consequence of representing mobile automata in a geographic environment is that movement can produce a change in the locational topology of the agents. The rule set for neighbourhood delineation is based on the proximity of agents on a geometric network, where agents within a specified distance of each other are considered neighbours. At each time step, the topology and automata composition of the neighbourhood for each citizen agent is estimated with a buffer drawn around the location of each agent, and all individuals that fall within the buffered area are classified as neighbors.

9.4 Spatial N-Person Prisoner's Dilemma

The aim of a spatial NPPD game is to investigate social interaction behaviors and communication between n > 2 individuals at a shared location. In this model, the NPPD game is an abstraction of social interactions in a spatial neighbourhood, and, as a generalized application, does not represent a specific type of relational situation between the agents. The goal of the generalized NPPD game is to only simulate the processes of social interactions and determine whether a series of outcomes make the neighbours more cooperative and trusting. Any reasons why the agents share a common location and decide to interact is secondary to the actual processes of communication and altruistic decision-making.

Formally, a typical social dilemma can be considered an n-person game, in which each player has the same preferred option that does not change regardless of the actions of the other players. Every player has the same payoff structure and can choose to either cooperate, C, or defect, D. The payoff of each player who defects is represented as D(m), where m is the number of players in a social grouping who cooperate ($0 \leq m \leq n-1$). The payoff for each cooperating player is denoted as C(m). The social dilemma is then defined by the following conditions (Akimov and Soutchanski 1994):

1. $D(m) > C(m + 1)$: each player is better off choosing to defect rather than cooperate, regardless of how many players choose to cooperate on a particular play of the game.
2. $C(n) > D(0)$; if everyone cooperates, each player is better off than if everyone defects.
3. $D(m + 1) > D(m)$ and $C(m + 1) > C(m)$; the more players cooperate, the better off each player is, regardless of whether he chooses to cooperate or defect.
4. $(m + 1)C(m + 1) + (n – m – 1)D(m + 1) > mc(m) + (N – m)D(m)$; society as a whole is better off the more players cooperate.

Formally, each citizen agent will be a stochastic learning entity with three step memory, and a predetermined action strategy and action choice (C or D). In a neighbourhood of *N* agents ($n > 2$), the state of each citizen at time *t* is characterized by defection or cooperation. At each time step, the model calculates the neighbourhood of each agent and determines the total number of cooperators and defectors in that grouping. As the interaction proceeds, each agent sets his action choice according to the probabilities updated on the basis of the reward/penalty computed from the payoff functions, his neighbour's actions, and the influence of its action strategy. The reader is referred to Zhao et al. (2005) for a list of action strategies that have been used in NPPD simulations.

A set of proposed payoff curves for both the defectors and cooperators can be straight lines functions expressed as (Szilagyi, 2003):

$$D = -0.5 + 2x \tag{9.1}$$
$$C = -1 + 2x \tag{9.2}$$

The updating scheme is a set of functions that assign an action to a citizen agent probabilistically based on his behavior and the behaviors of his neighbours. The probability that an agent will choose cooperation or defection is adjusted according to a three-step memory appraisal of the interaction histories of agents evaluated with a weighted payoff, an average payoff for the neighbourhood, and a three-step memory coefficient of learning. The action state of each agent at time *t+1* changes whenever his derived payoff is less than the production function and the adjusted probabilities of either cooperation or defection is greater than its current action state. The reader is referred to Power (2009) for a detailed overview of the mathematical workings of the spatial NPPD.

9.5 Computational Implementation of the Proposed Model

The social functionality of the model involves the refinement of the NPPD component to consider the emergence of leadership both within localized spatial neighbours and throughout the modeling environment. Building on the research of Zimmermann and Equíluz (2005), adaptive leadership would be simulated according to the expected payoffs that each agent associates with tagged individuals, the payoffs received from game play, and the imitation of action strategies from the highest paid automata. The original work simulated the emergence of cooperation and leadership from multi-agent social interactions, but the reorganization of neighbourhood structures was a simple random selection of individuals for an agent to interact with at *t+1*. Neighbourhood adaptation related to the evolution of the configuration of the social networks of the agents, but the spatial topology was ignored. The proposed model must consider the nonlinear interrelationship between the social structure and spatial geometry to effectively simulate topological adaptation in a network of “spaces between individuals”. For a socio-geographical environment, it is also important to include administrative leadership with adaptive leadership as presented by Uhl-Bien et al. (2007). It is standard that a real world community would often have individuals in formal authoritative roles who dictate information diffusion and policy decisions from a top-down viewpoint. These could be local government officials (e.g mayor), clergy, and other institutional figures and groups. This can be implemented in a model during initialization by randomly selecting one or more citizens agents and setting them as administrative leaders. Initialization settings for the simulation runs will establish the macro-level norms by which the community functions, and the administrative leaders would facilitate the dissemination of these institutional conditions throughout the environment. For example, a fundamental heuristic could be “the level of social identity should approximate the payoff schema of all cooperation at time step *t+1*”. Tesfatsion (1998) refers to this condition as the social welfare of a modeling environment, where the action choices of the majority of the automata are based on communal considerations rather than individual rewards. It would be the responsibility of the administrative leader to remind citizens within his neighbourhood of this collective goal, and this exchange will influence to varying degrees the decision-making of the citizens in their social interactions.

In a working model, the processes that define the environment will be simulated in sequential order. First, the spatial dynamics of agent mobility are simulated relative to expected payoffs and the action state of the automata at *t-1*. Given their strategy and action choice state, the expected payoff that an individual associated with another citizen is computed from the payoff functions. However, bounded rationality sets the condition that a citizen can only estimate the action choice states of their tags and the overall C leader, so computed expected payoffs are limited to these individuals. The computation of all payoffs in NPPD requires a minimum of three agents in the neighbourhood, but an agent would only know at most the action state of two game participants (himself and the tag or C-leader). Expected payoffs can be reliant on setting the action choice of the unknown neighbours with a random assignment of either cooperation or defection, and computing the reward or payoff from the utility functions. An underlying assumption is that C followers will seek out the C-leader(s), because they know there is at least one possible cooperator in the potential neighbourhood and other followers are likely to move to this location for the same reason. This set the probability that the percentage of cooperation in the neighbourhood could be higher, which results in a positive payoff for the agents. Defectors will also consider movement to the C-leader position in search for possible cooperators to exploit. The contrary situation exists for the expected payoffs assigned to the D-leader(s) who are flagged for their previous selfish action choices. The mobility component can have a set of transition rules that considers all expected payoffs in an agent's decision to move to a destination, but the movement decisions should also be subject to a random perturbation to simulate stochastic responses from the citizens. In the situations where the expected payoffs are minimal, the agent will be placed at a randomly selected destination. Mobility rules are also essential for the D-leader and C-leader. The uncooperative reputation of the D-leader makes him a target to avoid so he will have to constantly change position in search of a neighbourhood of citizens ignorant of his exploitive tendencies. The mobility rules for the C-leader should have a random condition that he will remain at his *t* location for the next time step. This rule increases the likelihood that the C-leader will be at the geographic coordinates chosen specifically by a follower for the purpose of interacting with him. At the start of each time step, a random number C_r can be computed, and the C-leader will travel to a new location when $C_r <= t_r$ or remain in place when $C_r > t_r$, where $t_r \in [0,1.0]$ is a model parameter set during initialization.

The modeling aspects for each time step of a simulation run can be explained by referring to agent *i* in figure 9.2. The initial decision of this citizen is a discrete mobility event to a destination, in this case a randomly selected building. Next, the model runs a buffering operation to determine the neighbours within a social network of fifty meters around the location of agent *i*. Thirdly, social interaction is modeled as a two-step process of information exchange and NPPD game play. The neighbours begin communication by diffusing their individual listing of tags amongst themselves providing each agent with a more refined and possibly expanded overview of the influential citizens in the socio-geographic community. Then, all agents in the local social network defined by the buffer engage in NPPD game play, each agent receiving a payoff conditioned on their interaction strategy

Figure 9.2: Example Social and Spatial Network Configuration for a NPPD Episode

and action choice. The cumulative utility level assigned to each agent after the game play can be considered as a measurement of their self-identity in the environment. The final modeling aspect is social mimicry, where agent *i*, if unsatisfied with their payoff, will imitate the action strategy of his highest paid neighbour. All agents will compute their aggregate payoff from the NPPD event, diffuse these scores throughout the neighbourhood, and identify the C and D leaders. The neighbourhood C-leader will be the agent with the highest payoff among all cooperators while the D-leader has the highest payoff of all defectors. The C and D leaders are spatially identified in the neighbourhood (see figure 9.2), and each agent will update his listing of tags to include these highest paid individuals. Agent *i* will then revisit his strategy by adopting the action strategy of the neighbour with the highest payoff. If there is more than one neighbour with the same maximum payoff other than agent *i* himself, then one is selected randomly. Agent *i* will retain his strategy if he has the highest payoff. For example, agent *i* receives a cumulative payoff of 0.4 from his Pavlovian action strategy, but a neighbour gets a reward of 0.9 from a greedy strategy. Agent *i* abandons the Pavlovian in favour of the greedy strategy for the *t+1* round of NPPD game play.

At the end of each time step, the administrative leader is tasked with a secondary role of communicating the identities of the overall C and D leader and the level of social identity for the environment. A simple comparative routine can identify the overall C and D leaders and compute the level of social identity as the average payoff of the individual levels of self-identity. This information is then diffused back through the social network to qualified individuals. A disqualifying condition can penalizes consistent defectors who ignore the administrative leader's suggestion to cooperate by refusing to provide this knowledge to these exploiters for a number of time steps.

The last modeling operation at time *t* is the updating of the social and spatial structure of leadership in the mapping display as shown in example in figure 9.3. Visual inspection of the mapped results at the end of each time step can aid in the identification and analysis of emergent patterns of leadership for various simulation parameters.

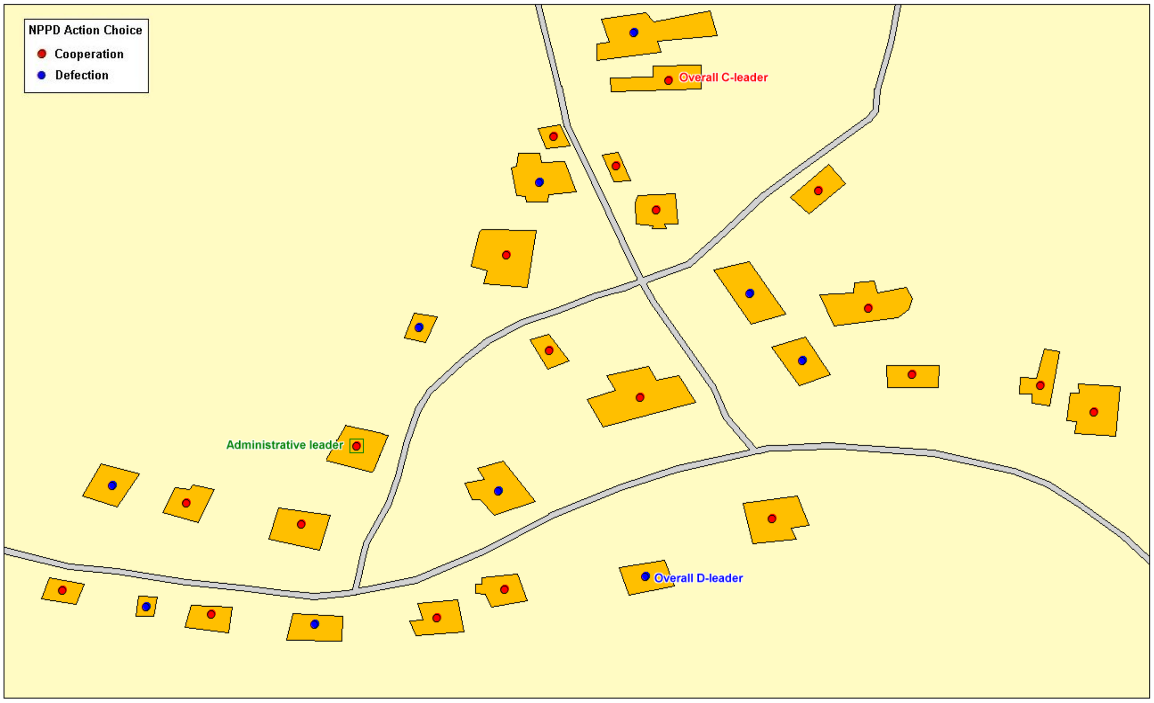

Figure 9.3: Example of Patterns of Cooperation and Leadership from a Simulation

9.6 Discussion

The goal of the simulation runs from the model is to experiment with "what if" scenarios (e.g. what if the all leaders are set as non-mobile) concerning the emergence of leadership within a socio-geographic community. A primary condition for the emergence of leadership is enabling and analyzing tensions in the social interactions of the citizens during simulation runs. Tension is theoretically present in the NPPD as individuals are often conflicted with the decision to either behave selfishly or cooperate with each other for the collective good of society. However, adaptive tensions can be introduced into a simulation with initialization settings and conditional rules that help motivate and coordinate the social interactions. Schreiber (2006) discusses enabling dynamics in emergent leadership in social groupings, and classifies leaders as agents who are most likely to communicate new knowledge.

After each time step, a source of new knowledge is the individual tag listing, and a heuristic can be set that this information is only shared with trusted neighbours. Tension is easily introduced into the information dissemination processes of the administrative leader. By combining each agent's listing of tags, the administrative leader can direct certain information to specific agents. For example, the level of social identity may be communicated to targeted defectors to encourage and remind them to consider cooperation at $t+1$ for the betterment of the social network. Also, the identity of the overall C and D leaders can be restricted to the followers with the lowest aggregate payoff to improve only their likelihood of moving to a neighbourhood of cooperators at $t+1$.

Zimmermann and Equíluz (2005) established that multi-agent Prisoner's Dilemma social networks enter a steady or equilibrium state when the network configurations and individual strategies remain stationary over a set time period. In these cases, agents have either received the maximum payoff in their neighbourhoods or they have all imitated the action choice strategy of the same agent. An additional factor when considering mobility and the spatial topology of social networks that enter a steady state is the role of context preservation on the emergent patterns of communal cooperation. Context preservation is a process where the configuration of a social and spatial neighbourhood remains static over a period of NPPD interactions. Cohen et al. (1998) state that context preservation increases the likelihood of local influencing (the tendency of players who interact frequently to become more similar over time) and homophily (the tendency to interact more frequently with the same individuals). Model experiments can be designed to investigate how the dynamics of adaptive leadership are swayed by the mobility status of the citizens and neighbourhood structures of social interactions. Power (2009) demonstrated that the preservation of neighbourhood context in non-mobile citizen agent environments produced larger clusters of cooperators than mobile agent environments. As the fixed citizen agents continuously interact with the same neighbours, they become homophily automata with increasing probabilities of copying the action of the majority of their social grouping. It is hypothesized that emergent levels of social identity would be higher for an environment of non-mobile citizens, but permanently fixed automata are an unrealistic dynamic for a socio-geographic community. Yet, the non-linear entanglement of the processes of self-organizing leadership and context preservation can be modeled with simulations where specific agents remain stationary under certain conditions. In a town meeting perspective, the administrative leader can be placed at a civic facility for a period of time to assume the role of a top-down mediator and disseminator of knowledge and policy options, and the majority of the citizens purposely travel to that location for social interaction purposes. Also, the overall C leader can be temporarily immobilized as long as his cumulative payoff is the highest of the C agents. He will become mobile whenever the payoff of another C agent is higher than his utility level for that time step. This condition is also appealing in a modeling sense in that the followers who chose to travel to the location of the C-leader will know that he is at those spatial coordinates. It is likely that geographic clusters of social cooperation and the network configuration of leadership will become more directly influenced by context preservation when agent mobility is restricted.

9.7 Conclusion

This paper presents a conceptual formulation of a spatially explicit agent-based model of cooperation and emergent leadership in a socio-geographic environment. The basic principles of the self-organization of social networks driven by tensions in the interactions among agents and emergent cooperation within the environment are central to the proposed framework. Self-organizing leadership requires a framework that entangles administrative and adaptive leadership in an environment where individuals can introduce and enable conditions that catalyze the emergence of a leadership structure. Enabling leaders are often the people who communicate new information to the social network, and this shared knowledge can induce selfishly oriented individuals to make cooperative decisions for the benefit of the community.

The modeling aspects are presented in a manner that details the integration of social and spatial components to simulate the non-linear interactions that occur within the relational space between agents. Leadership emerges in the environment from the tensions in the decision choices of citizen automata during NPPD play and the enabling actions of administrative and C-leaders. The mobility choices of unsatisfied agents are contingent on the possibility of a positive payoff from interactions with identified tags and C-leaders, where followers purposely move to the locations of these influential cooperators. During NPPD play, agents will be inclined to cooperate when the context preservation of the spatial network provides a degree of social familiarity among the neighbours. Familiarity strengthens relationality in the social network, one potential result being individuals' self-identities approximating the communal social identity. Evolutionary learning is embedded in the interaction dynamics of the agents in the form of social mimicry, which conditions low scoring followers to imitate the action strategy of the neighbours with the highest payoffs. The emergent leadership structure can direct this social mimicry of action strategies as followers imitate the strategies of C and D leaders. The well-connected community can be described as an environment of interacting agents in localized spatial neighbourhoods who cooperate for the benefit of the community according to the tensions, diffused knowledge and action choices of tags and leaders.

It is important to note that the intention of this paper is to present the theory of self-organizing leadership and cooperation in a socio-geographic environment. The working of a formal model of leadership is demonstrated as a component of the comprehensive model of social relationality discussed in the next chapter of this thesis.

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10.0 Paper 5: A Spatial Agent-Based Model of Social Relationality: Emergent Cooperation and Leadership in Community Development.

Abstract

This paper presents a spatially explicit agent-based model that simulates the social relationality underlying the principle processes of community development in a socio-geographic community. The formalization is based on the postulate that cooperation and leadership emerge from the behaviours of mobile affective agents as they participate in social interactions. The model is a process-centric system of integrated psychological, spatial, social, and labour market components. Each agent is an approximation of a human person with a layered model of affect simulating their personality, mood, and emotional states from the outcomes of social exchanges. Spatial mobility consists of daily activity events of agents moving between origin-destination locations relative to their states and expected payoffs from potential neighbours. The emergence of cooperation from social exchanges in most spatial neighbourhoods is modeled with the N-Person Prisoner's Dilemma. A spatial labour market game simulates employee-firm interactions with a preferential partnership matching mechanism and Iterative Prisoner's Dilemma employment. Self-organizing leadership depends on the tensions in the social interactions with leaders of cooperation and defection emerging as the successful agents with the highest payoffs. The unsatisfied agents undergo a form of evolutionary learning to survive in the social network by mimicking the action strategies of the highest paid individual in their neighbourhoods.

The advantages of the model are illustrated with a benchmark simulation of a real world community. Results show that a reward received from an interaction sets an agent in a positive affective state, and the relationality required for a form of steady state cooperation is directly linked to context preservation of the interaction neighbourhoods.

10.1 Introduction

Many studies in human geography are premised on the concept of social relationality between people across space and place. Lichtenstein *et al.* (2006) describe social relationality as an emergent phenomenon from the non-linear interactions that occur within the "spaces between" individuals in a social network. In this context, space is a sociological concept concerned with the sense of closeness that emerges from the communications and knowledge exchanges between individuals. The social aspects of the "space between" individuals are shared with the relational view of space of geographic complexity (Manson, 2007), but the locational variability of where the individuals are situated when they engage in a social interaction differentiate the approaches. However, several researchers (Gilchrist, 2000; Onyx and Leonard, 2010) present relationality as an emergent dynamic within a "well-connected" community, an interaction space that is both a sociological subject and geographic object. A complexity perspective on a relational community is a geographic confluence of social engagement across multi-scalar interaction networks of autonomous individuals. The self-organization of the internal structure of a community will depend on the social behaviours and spatial positioning of the individuals in the interaction networks as each person goes about his daily life.

In a relational community, the everyday activities occur within different types of social structures (dyads, small groupings, etc.) as power relationships, where the decisions and behaviours of affective individuals are controlled or influenced to varying degrees by certain authoritative figures. Incidental meetings, such as a retail event, are usually characterized by mutual control among the participants in the social network, because the exchanges between people are impersonal and short lived. Habitual activities, such as a work day, are interaction episodes where the same group of people is relationally connected for an extended period of time. There is an implicit correlation between higher intensities of control of social interactions at the habitual daily activities, because the familiarity that an individual has from dealing with the same people will better enable him to trust one of them as a social leader.

Spatial positioning in a community refers both to where the individuals are located and the mobility dynamics. The geographic extents of the community fluctuate with the movement of people as they travel to distinct locations to engage in activity specific social interactions. The destinations for these movement episodes, often buildings, provide a locational point of reference for the social interactions.

The dynamics of social relationality demonstrate that a community is a complex human system, consisting of many spatially and temporally varied processes directed by the sometimes stochastic and unpredictable decisions and behaviours of individuals. Therefore, the computational design of a model of a community requires a bottom-up approach for simulating the processes of social relationality according to the behaviours of affective individuals that generate a complex macro-level system structure. This paper presents a formalization that simulates a community as a spatial agent-based model of social relationality. As a complex adaptive system, a model of a well-connected community must represent the individuals, define the relationality between them according to a set of theoretically supported assumptions, and identify the spaces in which they exist and are related.

Gilbert (2004) suggests that the design of an agent-based model should consider existing theory to articulate its purpose, and its baseline architecture should concentrate on a number of important aspects in the theoretical application. Gilchrist (2000) presents community development as the complex processes of people networking and the formation of links and alliances that result in a sense of community. The well-connected community is formalized as a complex system of multi-scalar relationships and social interactions that lead to the emergence of communal decision-making and problem solving. In practice, community development is a specialized goal-oriented form of social relationality where the activities of the participants are geared towards improving the cultural, social, and economic conditions of a region. However, the generic framework of social relationality in this model is limited to several principle processes of community development specifically with mechanisms that simulate social interactions, cooperation, leadership, and collaborative behaviours.

Simulations of social, psychological, economic, and spatial dynamics are investigated and presented as separate but interrelated components of the system. The paper begins with an abstraction of community development as a star-like process, with each point of the star representing a specific modeling process. Section 10.3 presents the model architecture and dedicates considerable attention to the theoretical and computational implementation of the major processes. In section 10.4, the capabilities of the model are demonstrated with a benchmark simulation scenario. The paper concludes with a commentary on the benefit offered by agent-based modeling for the study of the social dynamics of human systems.

6.2 Complex Community Development

Onyx and Leonard (2010) describe community development as a complex system of nonlinear processes that emerge from the actions and initiatives of people as they utilize the embedded social capital within a community. For this study, the socio-geographic community presented by Power (2009) is the environmental setting of the model, and is implemented as both a geographical object and a sociological subject.

Following Shaffer *et al.* (2006), community development is conceptualized as a star-like constellation of interacting spatial, economic, psychological, and social processes (Figure 10.1). At the top of the star, the human resources are the population of individuals: each with a personality, mood, and emotional state, and each characterized by state variables that determine his social position and spatial location. The decisions and behaviors of each citizen will modify their affective conditions and state variables according to a set of transition rules and institutional

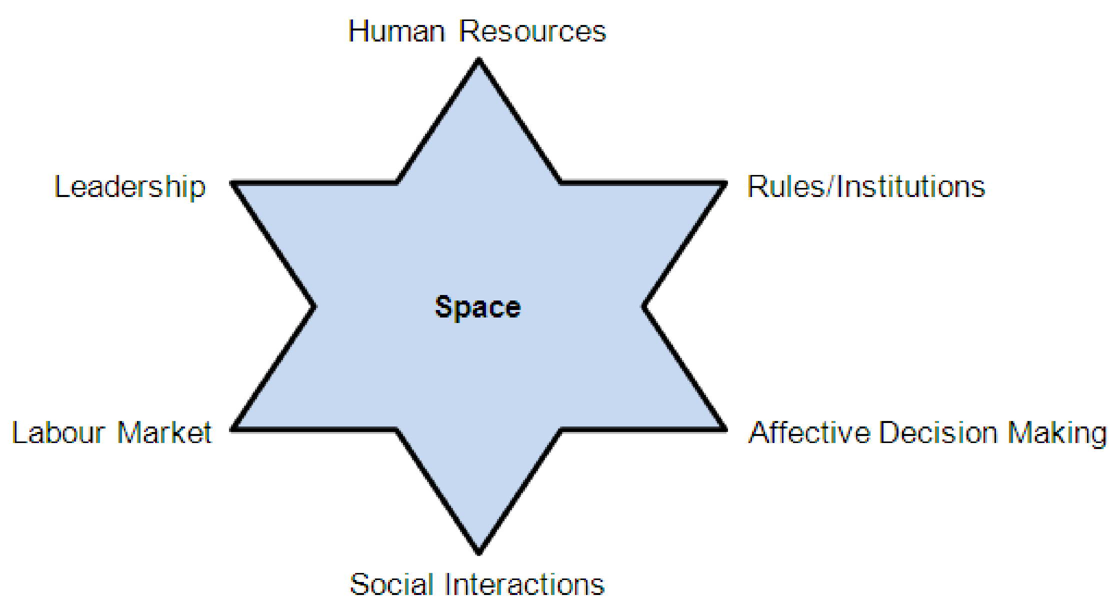

Figure 10.1: The Processes of Community Development

conditions. Due to feedback effects, the global consequences of these interactions ultimately affect the individuals.

Rules/Institutions guide the behaviors and decision making of the human resources. Institutions are governance networks that set the rules for using a community's social and labour market capabilities. Rules provide the agents with a form of intellectual ability to interact and communicate within the environment. Intelligence relates to an agent's cognitive ability obtained from its set of transition rules that handle its state, location, and neighbourhood interactions.

Decision-making is about choosing a course of action that is beneficial to both the individual and the community. An important underpinning of the decision-making process of community development are the social interactions between the citizens. These communication events enable individuals to learn about the opinions of others, gain knowledge about issues in the community, and participate in developing and implementing a development plan. A standard technique for the agent-based modeling of emergent cooperation is the Prisoner's Dilemma, both in environments consisting of many individuals and in those characterized by dyadic pairings. Yet a major shortcoming of conventional implementations of the Prisoner's Dilemma is the failure to incorporate the affective state of the agents as they engage in the social interactions. The emotional and mood states of individuals will influence their decision to cooperate or defect, as well as determine their reactions to the outcomes of these communication events. Decision-making can be implemented as an affective iterated Prisoner's Dilemma game.

Social interactions are directed tied to decision-making when agents have chosen to pursue an activity in the community that brings them in close proximity to other agents. Social interactions are the knowledge exchanges that occur amongst the individuals, and the results of these exchanges will determine the cooperation and leadership structure in the community.

Synergy in the labour market is an important factor in the economic conditions of a community. Agent-based labour market interactions have been simulated as Trade Network Games (Tesfatsion, 1997; 1998; 2001; Kitcher, 1998; McFadzean and Tesfatsion, 1999; Pingle and Tesfatsion, 2001, Hauk, 2001), and this approach was adopted but modified to consider the geographic distance in the evaluation of expected payoffs for preferential partnership matching. The spatial labour market game component simulates a two-sided market of employees and firms with preferential partnership matching behaviors and the option of non-employment. Cooperation emerges from the relationality and trust between pairings of agents as they participate in Iterative Prisoner's Dilemma game play.

Lichtenstein et al. (2006) describe leadership as an outcome of the tensions in the relational interactions among agents within a social network. Tensions are interjected into the social network when leaders enable rather than dictate the dynamics of social interactions by encouraging individuals to go against the status quo. Dictating can be socially restrictive, because the leader is telling the individuals to behave a certain way. However, leaders enable by allowing individuals to express their opinions, and this increases the possibility of the introduction of a radical idea or course of action to the social grouping. The modeling of self-organizing leadership requires the combination of the bottom-up enabling of adaptive leadership with the top-down conditions of administrative leadership. Adaptive leadership is based on the tensions in the Prisoner's Dilemma social interactions where individuals must evaluate the likelihood of a positive payoff to decide whether to cooperate or defect. Administrative leadership considers the influence of respected individuals in the dissemination of information and opinions throughout the environment. The emergence and sustainability of cooperation in the environment depends on the survival and reputation of the overall cooperation leader and the mimicry of the highest paid action strategies by unsatisfied agents.

Space is the central coordinating element that integrates all of the aforementioned processes, because all instances and manners of social interactions happen somewhere within the geographic confluence of the community.

10.3 Architecture of the Generic Model

The generic model is developed as an experimental approach for simulating the behaviours of affectively enabled agents in an artificial modeling environment. The model is generic in that it can in principle be applied to any community as it is built on methods that simulate the basic processes of social relationality.

Within this object-oriented modeling framework, agents are objects that use their definition and states to simulate behaviors. The architecture is comprised of activity-specific rulebases that model the mobility and social interaction dynamics of the agents.

10.3.1 Agents Objects and Agent States

Each agent is represented as an object that changes its main states variables and location according to transition rules at each time-step. For a socio-geographic community, this object-based view consists of both fixed and mobile geographic agents. The mobile agents are the individual citizens who move about in the environment to perform their daily activities. At the initialization of a simulation run, each citizen is assigned state variables that determine their social and economic profile. Citizens also have labour market and affective states that set the conditions for their participation in social interactions and records their responses to the outcomes the interactions. The fixed agents are buildings and structures that are directly geo-referenced as origins and destinations of the citizen agents.

10.3.2 State Transition Rules

The general state transition rules maintain and update the socio-economic profile of the citizens. One set of rules is concerned with altering the employment and participation status in labour market events. Additional rules update the action choice and affective states of the agents at the end of each time step. The default rule set is utilized to randomly select an activity for the agents to pursue at each time step.

10.3.2.1 Movement Rules

Movement is coordinated as discrete choice event simulations with a scheduling mechanism directing the agents' mobility behaviors (Zeigler *et al.*, 2000). Mobility rules manage the everyday activities, which are limited to church, recreation, retail, service, friendship gathering, school, or labour market events. Mobility is a relocation process of the agents' movement between a pair of origin and destination locations. In the spatial network, the agent moves to the location of a building containing the selected activity. However, the choice of building for this movement event can be directed with a measure of expected payoff from social interactions with agent(s) that are likely to be situated there.

10.3.2.2 Interaction Neighbourhoods

Agents interact with others in their neighbourhood. The rule set for neighbourhood delineation is based on the proximity of agents, where individuals within a specified distance of each other (a model parameter) are considered neighbours. At each time step, the topology and agent composition of the neighbourhood for each citizen agent is estimated with a buffer drawn around his location, and all individuals who fall within the buffered area are classified as neighbors.

10.4 Modeling Components of Social Relationality in a Community

The theoretical formalization of a community as a complex adaptive system of social relationality requires a framework that simulates the emergent spatial and temporal structures of cooperation and leadership from the affectively influenced decisions and behaviours of individuals pursuing everyday activities. Most of the social interactions are multi-person communication events, but the labour market interactions are dyadic exchanges between firms and employees. The model must also contain mechanisms dedicated to affective decision-making, leadership structuring, and social mimicry.

10.4.1 Social Interactions and Prisoner's Dilemma Cooperation

The magnitude of social identity in a community is contingent on the emergence of a level of cooperation within neighbourhoods of citizens and the diffusion of successful behavioral strategies and top-down administrative conditions throughout the network.

In the social and computer sciences, the Prisoner's Dilemma is a common method for analyzing the emergence of cooperation among non-relatives in social environments. A spatial Prisoner's Dilemma model assumes that cooperation emerges from the social exchanges that are guided by the manner in which the geographic structure of the environment influences the spatial behaviors of agents. Cooperation is consequently dependent on the neighbourhood relationality of each daily activity event. Labour market transactions require a directed bonding between employee-firm pairings where agents are matched relative to expected payoffs. This preferential matching sets a modeling constraint that the interaction between firms and employees is implemented on a one-to-one basis, where the firm agent exclusively and sequentially communicates with each employee in its neighbourhood. In a two-sided market environment, each potential employee-firm pairing is simulated as a two-person Iterative Prisoner's Dilemma (IPD) game.

During IPD play, two participants will play several consecutive rounds of the game using a payoff matrix to accumulate a total score (Trivers 1971; Axelrod 1984; Brembs 1996). The player with the larger cumulative score is deemed the winner and influences the cooperation strategy of the opponent. Through iterative play, cooperative and selfish behavior will typically be reciprocated to a certain extent.

The other daily activities represent social interaction events between groups of agents who are situated at the same location. These social interactions are many-to-many communication events in neighbourhoods consisting of $n > 2$ individuals, which are modeled with the N-Person Prisoner's Dilemma (NPPD). A typical social dilemma can be considered an n-person game, in which each player has the same preferred option that does not change regardless of the actions of the other players. Every player has the same payoff structure and can choose to either cooperate, C, or defect, D. The payoff of each player that defects is represented as D(m), where m is the number of players in a social grouping that cooperate ($0 \leq m \leq n-1$). The payoff for each cooperating player is donated as C(m). The social dilemma is then defined by the following conditions (Akimov and Soutchanski 1994):

1. $D(m) > C(m + 1)$: each player is better off choosing to defect rather than cooperate, regardless of how many players choose to cooperate on a particular play of the game.
2. $C(n) > D(0)$; if everyone cooperates, each player is better off than if everyone defects.
3. $D(m + 1) > D(m)$ and $C(m + 1) > C(m)$; the more players cooperate, the better off each player is, regardless of whether he chooses to cooperate or defect.
4. $(m + 1)C(m + 1) + (n - m - 1)D(m + 1) > mc(m) + (N - m)D(m)$; society as a whole is better off the more players cooperate.

10.4.2 Spatial Labour Market Game

The aim of the agent-based modeling of labour market dynamics is to simulate the patterns of employee-firms partnerships from the interactions of individuals under varied market conditions. The labour market component is a modified version of the Trade Network Game presented by Tesfatsion (1997; 1998; 2001) that incorporates spatial mechanisms into the labour market processes. The reader is referred to

McFadzean and Tesfatsion (1999) for a detailed overview of the components of the standard model. The original approach is revised to consider the geographic distance between agents in the partner selection in the labour market environment. In terms of specifications, the spatial labour market game is comprised of two methods: (1) a preferential partnership matching mechanism, where the mobility dynamics of the potential employees influence the submission of job offers, and (2) IPD employment. The preferential partnership mechanism is a spatially modified Gale and Shapley (1962) matching routine, where agents are paired by the expected payoffs that each individual associates with all potential partners. The spatial influence is included by reducing the expected payoffs according to the distance between the potential employee and firm. The potential employees then direct trade offers to firms they believe they can have a profitable social interaction with, and these firms utilize the same spatially modified Gale and Shapley assessment process to either accept or reject the offer.

The labour market game module simulates a two-sided market of employees and firms with choice and refusal behaviors and the option of non-employment. In the two-sided market, the set of *b* potential employees (agents who submit work offers) is disjoint from the set of *s* firms (agents who receive work offers). Therefore, the market structure is the union $V = B \cup S$ of the B subset of potential employees and the S subset of firms, where the potential employees can have up to *bq* work offers to the firms and the firms can accept no more than *sq* work offers from the employees, where *bq* and *sq* are parameters representing an offer quota and an acceptance quota respectively. For an interaction cycle, each potential employee and firm is randomly assigned initial expected payoffs for each of its possible partners and a preliminary worksite action strategy. A common choice in the standard framework is to set these utility levels equal to the mutual cooperation payoff from the Prisoner's Dilemma payoff matrix. For this study, the expected payoffs that the firms have for each potential employee are set in the same manner, but the expected payoffs that the potential employees have for each firm must take into consideration the distance between them.

The original research of Tesfatsion (1997) assigned action strategies to the agents as deterministic finite state machines for playing the employment game. However, a deterministic fixed action string is a limited tactic in simulating the behaviours of agents, because it assumes that all of the possible action decisions are represented by the transition functions in the finite state machine. It is also pragmatically difficult to represent affectively influenced and random decision making in the rigid structure of a deterministic routine. The finite state machine approach is substituted with a rule-based strategy that sets the probability of cooperation or defection according to a learning rate, memories of past payoffs, and the history of interactions with the neighbours. For model universality, the interaction strategies (see Table 10.1) are structurally the same for NPPD or IPD game play.

Table 10.1: Prisoner's Dilemma Action Strategies and Profiles (Zhao *et al.*, 2005)

Action Strategy	Action Strategy Description
Pavlovian	An agent with a coefficient of learning whose probability of cooperation changes by an amount proportional to the reward/penalty it receives from the environment
Accountant	An agent whose probability of cooperation depends on the average reward for the social grouping for a previous action.
Conformist	An agent who imitates the action of the majority in the social unit
Greedy	An agent who imitates the neighbour with the highest reward

For any agent v in V, v uses the expected payoffs $U_v(k)$ in the preferential partnering to determine the proffering, acceptance, or refusal of interaction offers based on the ranking of potential partners k. The spatial influence on $U_v(k)$ is dependent on the distance between v and k, the mobility status of v, and the neighborhood structure of k. A condition of the matching procedure is that agents have to be in close spatial proximity to submit work offers, which requires a movement event by an employee agent. Movement is penalized with a negative payoff dc that is subtracted from $U_v(k)$ to produce a spatially adjusted expected payoff value $Us_v(k)$. The firms are fixed agents while the potential employees are mobile agents. Therefore, the distance cost for firms is zero so their $Us_v(k) = U_v(k)$. For the potential employees, dc is computed as:

$$dc = \frac{Db_i(s)}{MaxD_{bs}}, \tag{10.1}$$

where i is the current location of agent b, $Db_i(s)$ is the road distance between employee b and firm s, and $Max\,D_{bs}$ is the maximum road distance between a potential employee and a firm, as calculated during initialization.

The potential employees within the matching neighborhood have determined that firm s is the most preferred tolerable employer at this stage of the matching process. As fixed entities, firms make no direct evaluation of employees before they are determined suitable by the degree of expected payoffs. Once judged, firm s's most preferred potential employees are placed on a waitlist while the remaining applicant neighbors are rejected by s and penalized a negative transaction cost payoff. Each rejected agent moves to the geographic location of the next most preferred tolerable firm who has not rejected him in the matching process and submits a work offer to this specific firm. If no tolerable firm exists, the agent returns to his residence, pays a distance cost from firm s_m to his residence, and takes a non-employment payment.

This matching process continues until firms stop receiving new trade offers, and the employees in their perspective waitlist are accepted for the employment process. For an employment event, the social exchanges between each pairing of employee *b* and firm *s* are simulated as an IPD game for that work cycle. Table 10.2 highlights the structure of the IPD payoff matrix. At the end of all labour market interactions for step *n*, all participants select an action choice according to the affective responses to the payoffs received from the interaction result, and the employed workers are relocated to their residence location.

Table 10.2: Payoff Matrix for the Spatial Labour Market Game

		Player A (Firm)	
Player B (Employee)		Cooperate	Defect
	Cooperate	1, 1	1, 2.5
	Defect	2.5, -1	-0.5, -0.5

10.4.3 Decision Making with a Layered Model of Affect

Affective decision-making is implemented as a psychological mechanism that simulates cognitive processes as a layered model of affect. It is designed to simulate the three interacting kinds of affect that occur in human decision making:

1. Personality – represents long-term affect and is defined by individual differences in mental characteristics. Personality is an atemporal state that generally remains constant throughout a life span of an individual.

2. Moods – reflect medium-term affect and have an influence on cognitive functions that decays with each successive interaction event.

3. Emotions – represent short-term affect and are usually associated with a specific event, object, or action. Emotions tend to dissipate when the agent changes focus.

The Personality-Mood-Emotion component utilizes the same layered approach presented by Gebhard (2005), but relates the emotional state of the agents to the results of social interactions. The specification of this module follows the standard methodology employed by numerous researchers (Egges *et al.*, 2003; Ghasem-Aghaee and Oren, 2003; Gebhard and Kipp, 2006; Mustafa *et al.*, 2008; Kasap *et al.,* 2009) of integrating the five factor model of personality, Mehrabian Pleasure-Arousal-Dominance (PAD) spacing mood determination, and the Ortony, Clore, and Collins (OCC) model of emotions.

10.4.3.1 The Big Five Factor Model of Personality

The five factor model summarizes the many ways in which people differ in their emotional and attitudinal styles with the five basic traits of Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism (McCrae and Costa, 1987; Goldberg, 1992; Judge and Bono, 2000):

- Openness (O). Open people are imaginative, intelligent, and creative. They like to experience new things.
- Conscientiousness (C). Conscientious people are responsible, reliable, and tidy. They think about all their behaviors' outputs before acting and take responsibility for their actions.
- Extroversion (E). Extroverts are outgoing, sociable, and assertive. They're energetic in achieving their goals.
- Agreeableness (A). Agreeable people are trustworthy, kind, and cooperative. They consider other people's goals and are ready to surrender their own goals.
- Neuroticism (N). Neurotic people are anxious, nervous, and prone to depression. They lack emotional stability.

A unique personality can be assigned to an individual by varying the values of each OCEAN factor within the range of -1 to 1. The appeal of the five factor model is the framework of OCEAN can be mapped to an individual's mood with Mehrabian PAD mood spacing.

10.4.3.2 Mehrabian Pleasure-Arousal-Dominance Mood Spacing

Mehrabian (1995) conducted a study to determine how his PAD temperament model could be theoretically linked to the five-factor model. He demonstrated how the commonality of descriptive emotional adjectives and measurement scales between the two approaches relate the three mood traits of Pleasure, Arousal, and Dominance to the five OCEAN components.

Mood is a medium term affect that decays with time so it can be computed as the average of a person's emotional states for a sequence of events and actions. In the PAD model, Pleasure, Arousal, and Dominance are orthogonal traits that form a mood space, which is implemented as a three dimensional Cartesian coordinate system with an axis ranging from -1.0 to 1.0 for each trait. The strength of each trait is the distance from the origin measures along the given axis, and the three distances setting the Cartesian positioning of the mood space. Mood is described with the following classification of each of the three mood space axis: +P and –P for the emotional state's positivity or negativity, +A and –A for mental arousal and alertness or mental inattentiveness, and +D and –D for feeling of social control and behavioral submissiveness. Table 10.3 lists all octants of the PAD mood space.

A factor in implementing mood is initializing each trait to position personality within a PAD spacing. Mehrabian (1996) devised a set of equations to translate the personality vector ***P*** into a default PAD mood spacing. The base mood of an individual is:

$$\boldsymbol{P} = O,C,E,A,N \in [-1,1]$$
$$Mood_{base} = P_1, A_1, D_1 \in [-1,1]$$

$$P_1 = 0.21E + 0.59A + 0.19N \quad (10.2)$$
$$A_1 = 0.15O + 0.30A - 0.57N \quad (10.3)$$
$$D_1 = 0.25O + 0.17C + 0.60E - 0.32A \quad (10.4)$$

Table 10.3: Mehrabian Mood Octants and Mood Types

Trait Combination (Octant)	Mood Type
+P +A +D	Exuberant
-P -A -D	Bored
+P +A -D	Dependent
-P -A +D	Disdainful
+P -A +D	Relaxed
-P +A -D	Anxious
+P -A -D	Docile
-P +A +D	Hostile

Russell and Mehrabian (1977) provide the methodology for simulating mood change from the association of PAD mood space to OCC emotions. Table 10.4 shows a portion of their suggested mapping for several basic emotions to specific PAD spacings. Each emotion type is described in terms of a set of values on the PAD axis that associates emotion to a PAD octant and mood type. For example, when a person experiences the emotion joy, the mood spacing will be adjusted so that the Pleasure, Arousal, and Dominance values are all positive, which puts him in an exuberant mood.

Table 10.4: Mapping from OCC Emotions to PAD Mood Space

Emotion	Pleasure	Arousal	Dominance	Mood Type	Mood Class
Joy	0.40	0.20	0.10	+P+A+D Exuberant	Positive
Distress	-0.40	-0.20	-0.50	-P-A-D Bored	Negative

10.4.3.3 Ortony, Clore, and Collins Model of Affective Emotions

Several authors (Ortony *et al.*, 1988; Bartneck, 2002; Kasap *et al.,* 2009) present the OCC model as the standard approach for emotion synthesis utilizing cognitive appraisal theory. Cognitive appraisal theory asserts that emotions are elicited and differentiated on the basis of a person's subjective appraisal of the significance of a solution, object, or event from a set of criteria (Scherer 1999). Emotions are the reactions to three types of appraisals: the appraisal of events with respect to agent goals, the appraisal of agents with respect to the praiseworthiness of their actions compared to a set of standard behaviours, and appraisal of objects from the appeal as determined by agent attitudes. Ortony (2003) states that the development of an affective model with the original hierarchy of twenty two emotions is computationally impractical, and suggests using only the emotional categories those agents will experience during the modeling events.

The methodology of both the IPD and NPPD is such that the emotions experienced by the agents can be valenced reactions to the consequences of Prisoner's Dilemma events and the actions of agents towards cooperation or defection. The event-based emotions in Figure 10.2 emerge when an agent determines the consequences of game play as being either desirable or undesirable. Desirability sets the intensity of event-based emotions and is the main criterion for evaluation. The intensities of the prospect-based emotions are set before Prisoner's Dilemma play begins as a probabilistic appraisal of the hope of receiving a reward or the fear of a penalty from past memories of exchanges with neighbours. The well-being emotions of joy and distress are directly measured from the outcomes of the Prisoner's

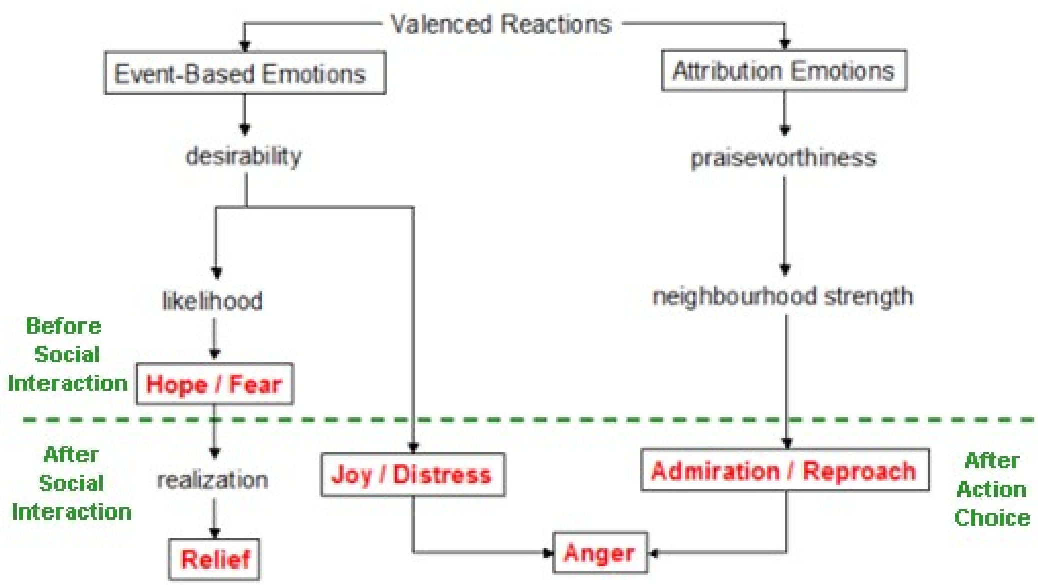

Figure 10.2: OCC Emotions for IPD and NPPD Game Play

Dilemma events: joy with a positive payoff and distress with a negative result, the intensities of each conditioned on the magnitude of the assigned utility value. The right branch of Figure 10.2 contains the affiliation emotions of admiration and reproach, and they are caused by reactions to the actions of agents that are evaluated as being either praiseworthy or blameworthy. These emotions are computed after a social interaction event, and their intensities will indicate the positive or negative affects of the level of emergent cooperation in each interaction structure.

The final affect is anger, which is a compound affiliation emotion that is measured from the conjunction of the negative conditions of distress and reproach. The intensity of anger depends first on an agent's reaction to receiving a penalty, and then on the amount of blame placed on the decisions of others. Thus, the computation of anger occurs at the end of each social exchange once the agents have made an action choice.

10.4.3.4 Rule Based Inference of Affective States Pre-Prisoner's Dilemma

The Personality-Mood-Emotions component is structured as a conditional rule-based system that simulates the affective states of agents from their daily activities, neighbourhood configurations, and cooperation decisions from the outcomes of social interactions. The prospect based emotions of hope and fear depend on the degree to which a social exchange is pleasing or displeasing to an agent, but also must be appraised from the likelihood of getting a reward. For these anticipative affects, the likelihood of an event must be weighted by the desirability of the expected event outcome. The activation of a prospect emotion requires the determination of its Personality-Mood-Emotions intensity *(I_{PME}),* and this relies on the emotional intensity I_E computed from likelihood and desirability of a potential payoff, the intensity of temporal mood PAD state (I_M), and, sometimes, the degree of neuroticism of the agent. The level of I_E for hope is high whenever the likelihood and desirability are both high. As likelihood decreases, the intensity of hope decreases to the point that the effect of desirability is negated. Fear is initially assigned an I_E setting referring to the likelihood of getting a negative payoff. The higher the likelihood, the more intense the level of fear.

The combined affective intensities of joy, distress, relief, admiration, reproach, and anger at time step *t* are embodied in the mood PAD spacing, which is a contributing factor in setting the overall affective state and action choice of an agent at time step $t+1$. A positive mood space value I_M raises the intensity of hope and decreases the intensity of fear a random amount while the contrary situation occurs for a negative mood state. Secondly, the temporal mood state becomes the default means of setting the I_{PME} whenever the level of I_E is negligible or zero.

In situations where I_E and I_M are both approximating zero, the long term affect of the neuroticism of an agent will influence the computed $\mathrm{I}_{\mathrm{PME}}$ level. By their propensity to be easily stressed and overreact in social situations (Miller, 1991), extremely neurotic individuals will be less hopeful and more fearful and their corresponding affective intensities will be lessened and strengthened accordingly. The opposite condition applies to individuals with low neuroticism levels.

At the completion of the pre-Prisoner's Dilemma affective state evaluation, the comprehensive intensity values I_{Hope} and I_{Fear} values are passed to simulate affective Prisoner's Dilemma interactions.

10.4.3.5 Affective NPPD and IPD

Each agent is characterized by a stochastic learning process, a two period memory, a predetermined interaction strategy, an action choice (C or D), a personality, and a default mood PAD spacing. At each time step, each agent adjusts the probability of cooperation from his emotional state proportional to the reward/penalty he received from the environment, and the influence of his coefficient of learning.

The emotional fine-tuning of the probability of cooperation for an agent occurs before the choice of action. This fine tuning takes place before and after the agents receive a payoff for the interaction event. The probability of cooperation for agent *i* at time step *t*, $p_i(t)$, is reset before the payoff according to the agent's intensities of fear and hope, and afterwards as a function of relief, joy, and distress. The initial stage pre-payoff affective state is computed as:

$$I_{\text{prePayoff}} = (I_{Hope} + 0.1) + (I_{Fear} - 0.1) \tag{10.5}$$

The social interactions occur either as group exchanges or labour market pairings. Except for the labour market interactions, the payoff curves for both the defectors and cooperators are straight lines functions expressed as (Szilagyi, 2003):

$$D = -0.5 + 2x \tag{10.6}$$
$$C = -1 + 2x \tag{10.7},$$

where x represents the ratio of the number of cooperators to the total number of neighbours.

The payoff or reward for labour market exchanges is determined from the payoff matrix in Table 10.2. Once the agent has collected a reward or penalty, the post payoff intensities of relief, joy, and distress are computed, and the probability of cooperation is adjusted accordingly. Thus, the comprehensive post-payoff affective states is:

$$I_{Postpayoff}=(I_{Relief} + 0.05) + (I_{Joy} + 0.1) + (I_{Distress} - 0.1) \tag{10.8}$$

The emotional adjusted probability of cooperation for agent *i* is then set as

$$p_{ei}(t) = p_i(t) + I_{\text{prePayoff}} + I_{postPayoff} \tag{10.9}$$

and the emotional adjusted probability of defection is then calculated as :

$$q_{ei}(t) = 1 - p_{ei}(t) \tag{10.10}$$

The action strategy of an agent is based on the interaction history of the agents as represented by a weighted payoff, a coefficient of learning, and an average production function.

Given an agent, the weighted payoff is defined as

$$RPwt = \sum_{i=1}^{3} W_i Mc_i \text{, where } \sum_{i=1}^{3} Wi = 1 \tag{10.11}$$

and Mc_i is the historical payoff (Mc_1 stores the current payoff). Assuming that the effects of memory decrease with time, $W_1 \geq W_2 \geq W_3$.

Each agent is also assigned a coefficient of learning α_i, where $0 < \alpha_i < 1$, to adjust the probability according the responses of their neighbour(s) and past cooperation states. α_i increases if an agent continually cooperates or defects but decreases as the actions become varied.

With α_i restricted to the range 0.1 to 1, there are three possible adjustments to the learning coefficient:

4. $\alpha_i(t+1) = \alpha_i(t) + 0.10$, if $(S(t) = S(t-1))$ and $(S(t-1) = S(t-2))$
5. $\alpha_i(t+1) = \alpha_i(t) + 0.05$, if $(S(t) = S(t-1))$ and $(S(t-1) \neq S(t-2))$
6. $\alpha_i(t+1) = \alpha_i(t) - 0.05$, if $(S(t) \neq S(t-1))$

Consequently, the probability of cooperation for agent *i* at time *t+1* is:

$$p(t+1) = p_{ei}(t) + (1-p_{ei}(t)) * \alpha_i, \text{ if at time } t, \text{ action} = C \text{ and } RP_{wt} > 0 \tag{10.12}$$
$$p(t+1) = (1-\alpha_i) * p_{ei}(t), \text{ if at time } t, \text{ action} = C \text{ and } RP_{wt} \leq 0 \tag{10.13}$$

The probability of defection is thus computed as $q_{ei}(t) = 1 - p_{ei}(t)$.

The same set of equations is also used for updating the action probabilities when the previous action is D:

$$q(t+1) = q_{ei}(t) + (1- q_{ei}(t)) * \alpha_i, \text{ if at time } t\text{, action = D and } RP_{wt} > 0 \quad (10.14)$$
$$q(t+1) = (1-\alpha_i) * q_{ei}(t), \text{ if at time } t\text{, action = D, and } RP_{wt} \leq 0 \quad (10.15)$$

The state of agent i is updated contingent on its previous state, the average neighbourhood production function, and the probabilities for both C and D. The neighbourhood production function for time t is the cooperation payoff for the group computed as:

$$pf_i = \sum_{i}^{3} Cj / N \quad (10.16)$$

where C_j is the payoff value for agent j and N is the total number of agents in the neighbourhood.

Despite the preferential bonding in the dyadic social exchanges of the labour market transactions, the production function considers the cumulative payoffs for all participants within the employment neighbourhood. Formally, pf_i is computed in the same manner for all daily activity interactions.

The average neighbourhood function for three memory events is formulated as:

$$pf_{avg} = \frac{\sum_{i}^{3} pf_i}{3} \quad (10.17)$$

Thus, the state of agent *i* at time *t+1* with S(*t*):

For S(t) = C:

$$S(t+1) = \left\{ \frac{\text{D, if } RP_{wt} \text{ for agent i} < pf_{avg} \text{ and } p(t+1) < q(t+1) \text{ and } q(t+1) > R_u}{\text{C, retain previous action if the conditions for D are not satisfied}} \right\} (10.18)$$

For S(t) = D:

$$S(t+1) = \left\{ \frac{\text{C, if } RP_{wt} \text{ for agent i} < pf_{avg} \text{ and } q(t+1) < p(t+1) \text{ and } p(t+1) > R_u}{\text{D, retain previous action if the conditions for C are not satisfied}} \right\} \quad (10.19)$$

,where $R_u \in [0,1]$ is a uniform random value.

10.4.3.6 Rule Based Inference of Post-Action Choice Affective States

The intensities of affiliation emotions are set relative to the short-term, middle-term, and long-term valenced reactions to a social interaction result. Cooperation will depend greatly on admiration and reproach, because these affiliation emotions are indicators of the benevolent considerations between neighbours. The intensity of admiration increases as more neighbours choose cooperation as their action choice. The reverse situation exists for reproach as its intensity strengthens as the instances of defection increase in the multi-agent neighbourhoods and dyadic pairings. However, an emotional agent will tend to cooperate with those individuals he has an affective connection with, which is contingent on the context preservation in the neighbourhood (Cohen *et al.,* 1998; Szilagyi, 2003; Power, 2009).

The intensity of anger depends first on an agent's reaction to receiving a penalty, and then on the amount of blame placed on the decisions of others. Being partially derived from an affiliation emotion, context preservation is a necessary condition for the intensity of anger to be significant, because the distress of a negative payoff derived from the action choices of trusted neighbour(s) results in a compounded negative short-term affective state.

The post action choice emotions are also influenced by mood and personality with their intensities adjusted by mood class and neuroticism level. The modification in the intensities from the middle-term and long-term affective states is the same as previously discussed in section 10.3.3.4.

10.4.3.7 Mood Adjustment

Kessler *et al.* (2008) presents a mood updating component of the SIMPLEX emotion model that determines a mood state according to the average intensities of all activated emotions. The same approach is applied as a function that computes an average PAD spacing from the intensities of the triggered emotions from the result of a Prisoner's Dilemma event. Table 10.5 shows the comprehensive mapping of the OCC emotions and PAD space.

Table 10.5: Mapping of OCC Emotions to Mehrabian PAD Spacing

Emotion	**P**leasure	**A**rousal	**D**ominance	**PAD** Octant	Mood Type	Mood Class
Joy	0.40	0.20	0.10	+P+A+D	Exuberant	Positive
Hope	0.20	0.20	-0.10	+P+A-D	Dependent	Positive
Relief	0.20	-0.30	0.40	+P-A+D	Relaxed	Positive
Admiration	0.40	0.30	-0.24	+P+A-D	Dependent	Positive
Distress	-0.40	-0.20	-0.50	-P-A-D	Bored	Negative
Fear	-0.64	0.60	-0.43	-P+A-D	Anxious	Negative

10.4.4 Self-Organizing Leadership

Self-organizing leadership requires a framework that entangles administrative and adaptive leadership in an environment where individuals can introduce and enable conditions that catalyze the emergence of a leadership structure. The individuals who assume the role of a communicator receive a "tag" within the social network (Holland, 1995; Marion and Uhl-Bien, 2001) when they are recognized as influential in coordinating initiatives and facilitating interactions amongst the individuals. A tag represents the social standing or reputation associated with a leader due to the role he undertakes in catalyzing actions and directing behaviours in the social network. With the condition that a tag is often unassociated with a position of formal management, there can be multiple leaders who share the facilitator role in tandem. Administrative leadership is implemented by randomly selecting one or more agents during initialization and assigning them the authority and responsibility of disseminating all institutional information throughout the environment.

The emergence of cooperation depends on the inherent and introduced tensions in the social interactions of citizens. The temptation of a payoff for defection in the Prisoner's Dilemma interjects tensions into the action choice decisions of the agents. Tensions are also introduced into the social interactions with the probability that agents exhibit behaviors that are contrary to their expected payoffs. For example, an agent may decide to interact with a neighbour with the lowest expected payoff rather than the agent with the highest expected payoff.

At the end of each time step, all agents compute their self identity as the aggregate payoff from the daily activities, and the neighbourhood C-leader will be the agent with the highest payoff among all cooperators while the D-leader has the highest payoff of all defectors.

The administrative leader is tasked with a secondary role of communicating the level of social identity and the tags of the overall C and D leaders in the environment. This requires that each agent relay his listing of tags and self-identity to the administrative leader. A comparative routine identifies the overall C and D leaders and computes the level of social identity as the average payoff of the individual levels of self-identity. This information is then diffused back through the network to qualified individuals.

The overall C-leader is the highest paid cooperator within the environment, the one individual whose action strategy is considered optimal for the emergence of cooperation within the network. The emergence of global cooperative steady states will depend exclusively on the survival of the C-leaders with the maximum payoffs in the network, because these are the individuals that unsatisfied agents gravitate towards as they search for partners for future social interaction episodes. Also, the selfish nature of the agents will entice them to abandon their unsuccessful behavioral schemas and socially mimic the action strategies of the highest paid individuals to get a larger payoff at $t+1$.

10.4.5 Social Mimicry

Each unsatisfied agent first determines all C-leaders and D-leaders, if any, within his spatial neighborhood, and copies the strategy of the neighbour with the highest cumulative payoff. If there is more than one neighbour with the same maximum payoff other than the agent himself, then one is selected randomly. The agent will retain his strategy if he has the highest payoff.

10.5 Model Experiments

The object oriented model was developed in REPAST© Java (Figure 10.3). The model is spatially explicit in that it utilizes high resolution Geographic Information System layers to represent the elements of a socio-geographic community: building polygons, a linear road network, and citizen agents symbolized as points. A central feature of the model is the ability of the user to set the parameters for each of the components before the simulation runs. For example, the duration of each of the everyday activities can be varied to reveal the influence of context preservation on the emergent patterns of cooperation.

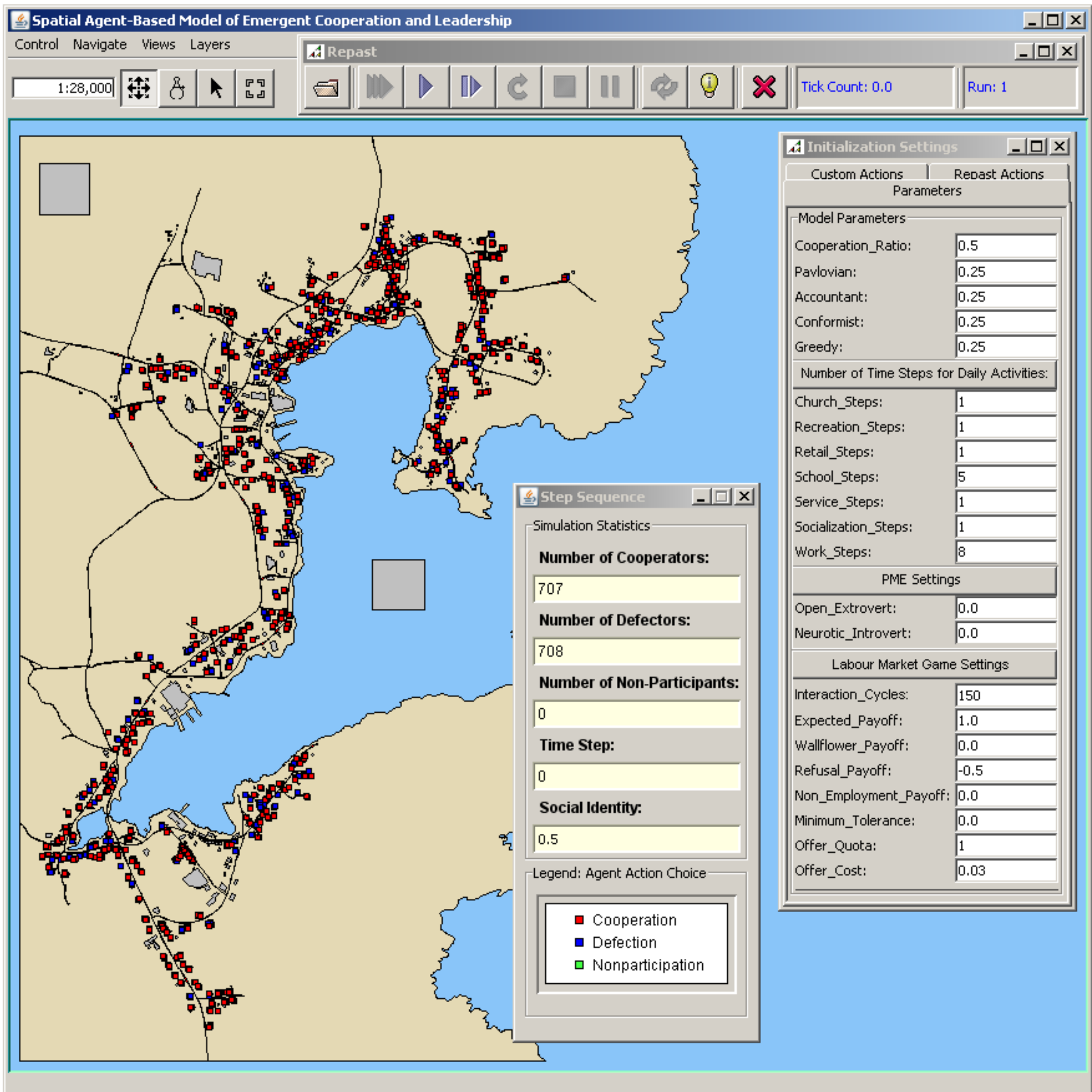

Figure 10.3: Model Interface and Default Parameters

10.5.1 Model Environment

The model is implemented through the simulation of social interactions in the community of Trinity Bay North, Newfoundland and Labrador, Canada (Figure 10.4). This study area was chosen because of the availability of spatial layers for each of the required features for a socio-geographic community and the availability of individual level socio-economic statistics to produce and assign state variables to each citizen agent. The buildings and roads are fixed agents, with the buildings having a single state that classifies them according to occupancy. Note that there are two additional polygons to represent the destinations for the employees who engage in fishing and who work outside of the confluence area of the community. Citizens (Figure 10.5) are mobile agents with states (age, occupation, etc.) that have been microsynthesized from selected 2011 Statistics Canada general census tables and ancillary datasets.

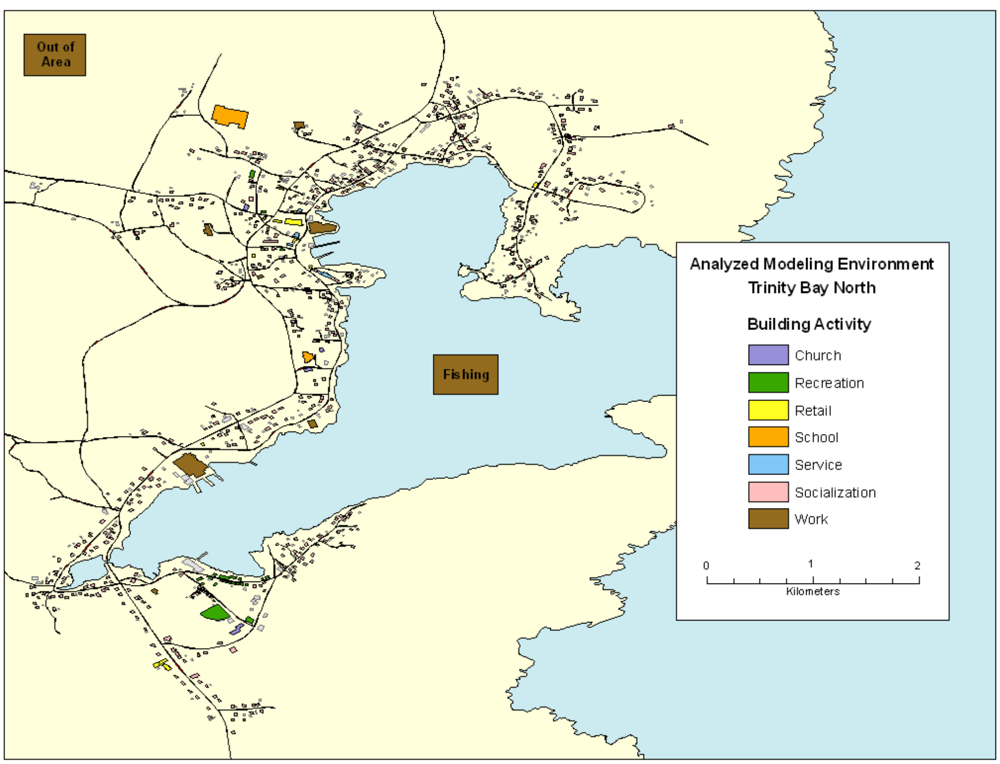

Figure 10.4: Analyzed Environment of Trinity Bay North

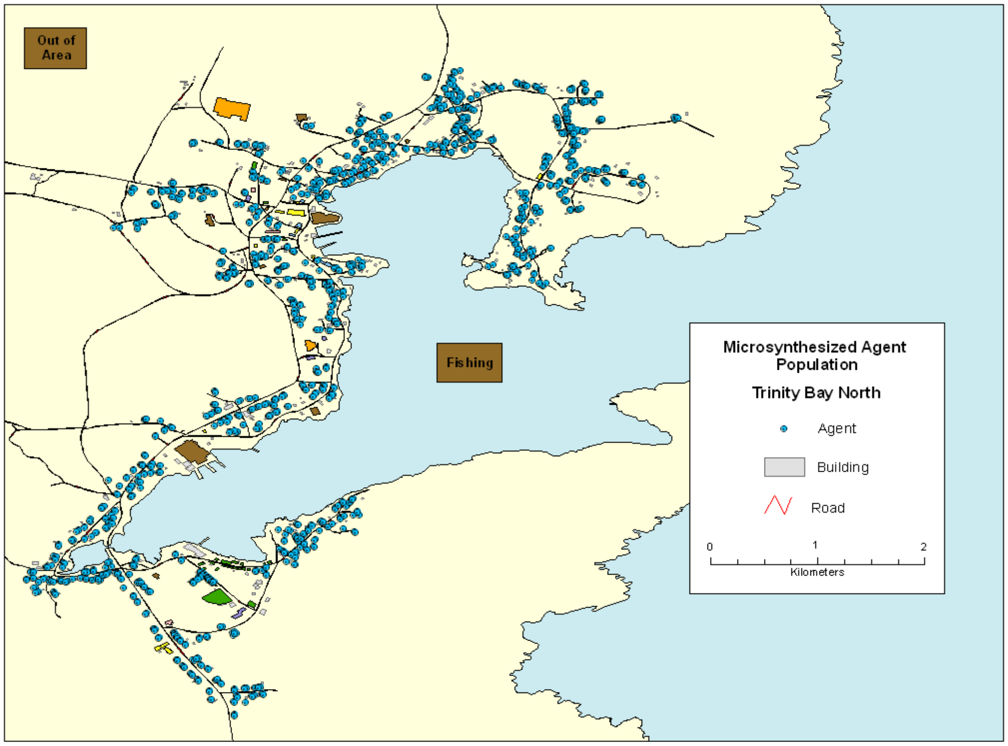

Figure 10.5: Microsynthesized Population by Household Structure

10.6 Simulation Results

As a benchmark evaluation, a simulation was run with the default settings as displayed in Figure 10.3. During initialization, the citizens are randomly selected and assigned an action strategy (see table 10.1) and a randomly generated OCEAN personality. The effect of context preservation on the cooperative structure of the spatial neighbourhoods is conditioned on continuous social interactions for school and work activities where the agents remain at these locations for 5 and 8 time steps respectively. The labour market parameters set the expected payoff for mutual cooperation at 1 and the wallflower payoff at 0. Also, all participant employees and firms are enticed to enter and remain in the labour market by setting the non-employment payoff to 0.

The inherent stochasticity of agent-based models makes the analysis of a single simulation result problematic. Therefore, the average result from 500 simulation runs is the basis for the analysis of the simulation outcomes. Each simulation run consists of 500 time steps of social interaction and agent mobility. However, the labour market interactions required secondary nested interactions of 150 labour market exchanges for each simulation time step. To illustrate for time step *t*, the firm is individually paired with each employee in its neighbourhood for 150 iterations of IPD game play, with the average utility level set as the resultant payoff for that labour market transaction. The following discussion is a summary of the average mobility activities, affective states, action choices, and leadership structure patterns.

Figure 10.6 is a line graph of the average action choices of the agents. With the exceptions at time steps 119 and 341, there are more defectors than cooperators in the socio-geographic community after each simulation step, but this is anticipated for two reasons. Firstly, the payoff structure of the Prisoner's Dilemma will encourage more defectors than cooperators, because citizens are tempted to behave as selfish individuals in the pursuit of the highest possible reward. Secondly, the mobility choices of many of the citizens involve single time step daily activities that require these agents to reevaluate their activity choices and geographic location at $t+1$. This persistent transient subpopulation of agents destabilizes the temporal constancy of many social interaction neighbourhoods so the level of trust and relationality known to contribute to communal cooperation is absent or significantly limited.

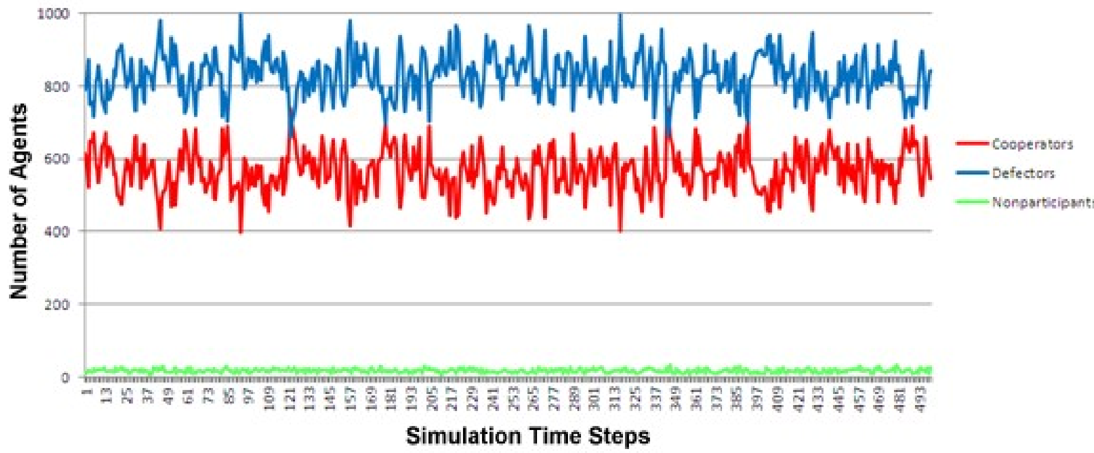

Figure 10.6: Simulation Summary of Action Choices for the Agent Population

A steady state of cooperation depends on a relatively stable agent membership in the interaction neighbourhoods and the adoption and utilization of the same action strategy by the individuals (Zimmermann and Equiluz, 2005). In this model, these factors are difficult to evaluate, because the single time step activities ensure that the neighbourhood membership of a considerable portion of the agent population varies from one time step to the next. Yet, the effects of context preservation can be analyzed at a time step when the total communal level of cooperation is high. For the 58% cooperation level of time step 119, the spatial dynamics of the social interactions are displayed on the map in Figure 10.7, especially in the insets centered on the locations of the overall C and D-leaders. Small geographic groupings of cooperators are evident throughout the environment, but the largest concentration of cooperation occurs at locations of activities where context preservation is intentionally introduced. It is logical that an overall C-leader will be spatially positioned within a preserved neighbourhood where cooperation dominates, because the memory adjusted payoffs of the agents will record any degree of trust that emerges within the localized social network. The noteworthy finding in Figure 10.7 shows the presence of multiple overall C-leaders, which supports the assumption of Marion and Uhl-Bien (2001) that multiple leaders can emerge as information facilitators in a social interaction network.

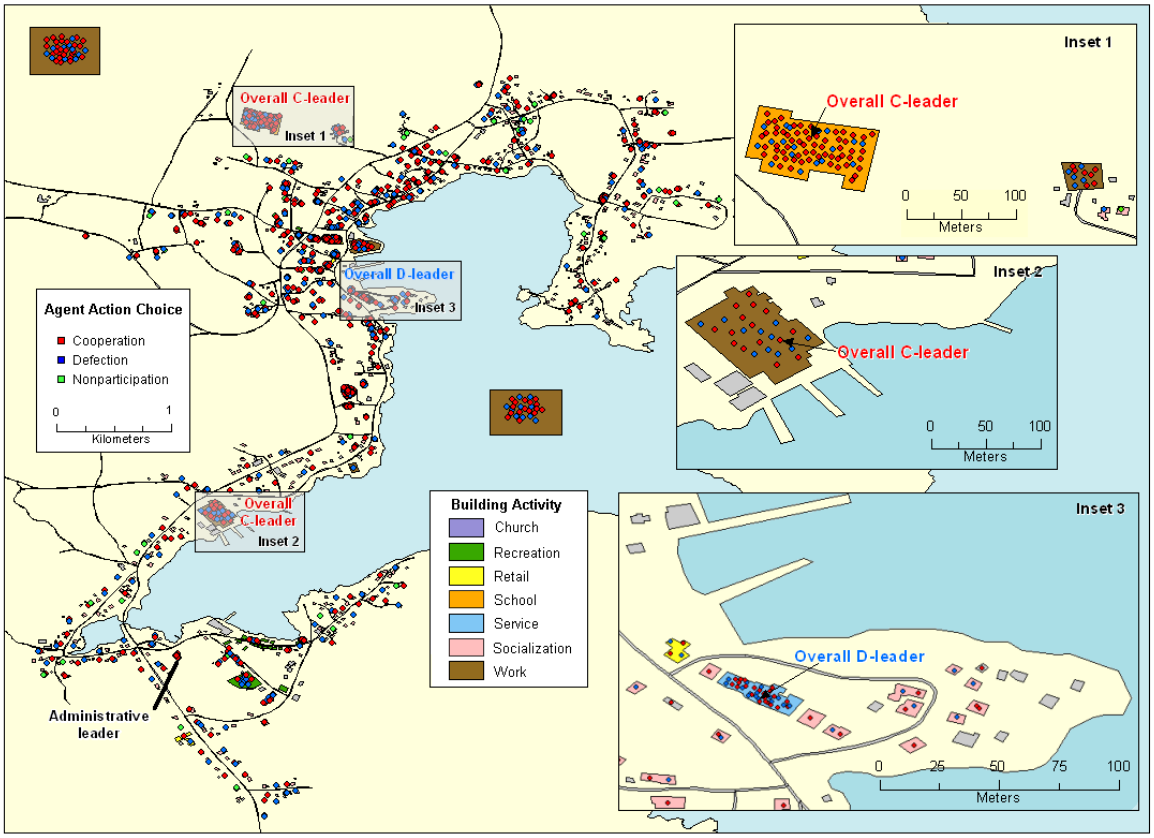

Figure 10.7: Average Cooperation and Leadership Structure at Sampled Time Step 119 for Simulations with Normal Personality Population and NEP=0

With two overall C-leaders, there is a greater probability that the expected payoffs will direct the lowest paid agents to one of these locations, which translates into more agents interacting with a selfless partner and possibly a higher incidence of localized cooperation.

The contrary social interaction dynamic exists for the overall D-leader who becomes tagged as the highest paid exploiter in the environment. The behaviour of the unsuccessful agents thus depends on the fact that the expected payoffs they compute at each time step sets the D-leader as the least attractive partner for social interaction. The probability of these citizens traveling to the location of the D-leader is low, but still stochastically possible. To counter this behaviour, the D-leader must be constantly mobile during the time sequence that he is the dominant defector to avoid reprisals from previous unsatisfied partners. The threat of reprisal is directly proportional to the degree of familiarity and context preservation in the localized social network so the overall D-leader will usually avoid participation in school or work events. This is one reason why the overall D-leader in inset 3 on Figure 10.7 is situated within a building of a single time step service activity.

With the mood spacing of an agent endowed with a three-step memory response, the most common average mood state provides a measure of the affective condition of each agent during a set of simulation runs. Figure 10.8 shows a ring diagram of the most common average moods for the simulation runs, with each bar containing bins for five PAD spacing assignments. For each time step, a wedge shows the mean percentage of citizens who have most frequently exhibited each particular mood during the simulations. For example, time step one displays a bin size of 16% for ***dependent***. This indicates that accumulating the results for the 500 simulations, at time step one, the dominant mood for 16% of the citizens was ***dependent***.

The affective structure shows that a considerable portion of the population is an exuberant mood due to the positive results from the social interaction events. With the payoff structure, the localized D-leaders are often the most exuberant individuals and remain in this mood state as long as they avoid reprisals for their egocentric behaviors. However, the prevalent mood space is ***dependent***, which signifies that the

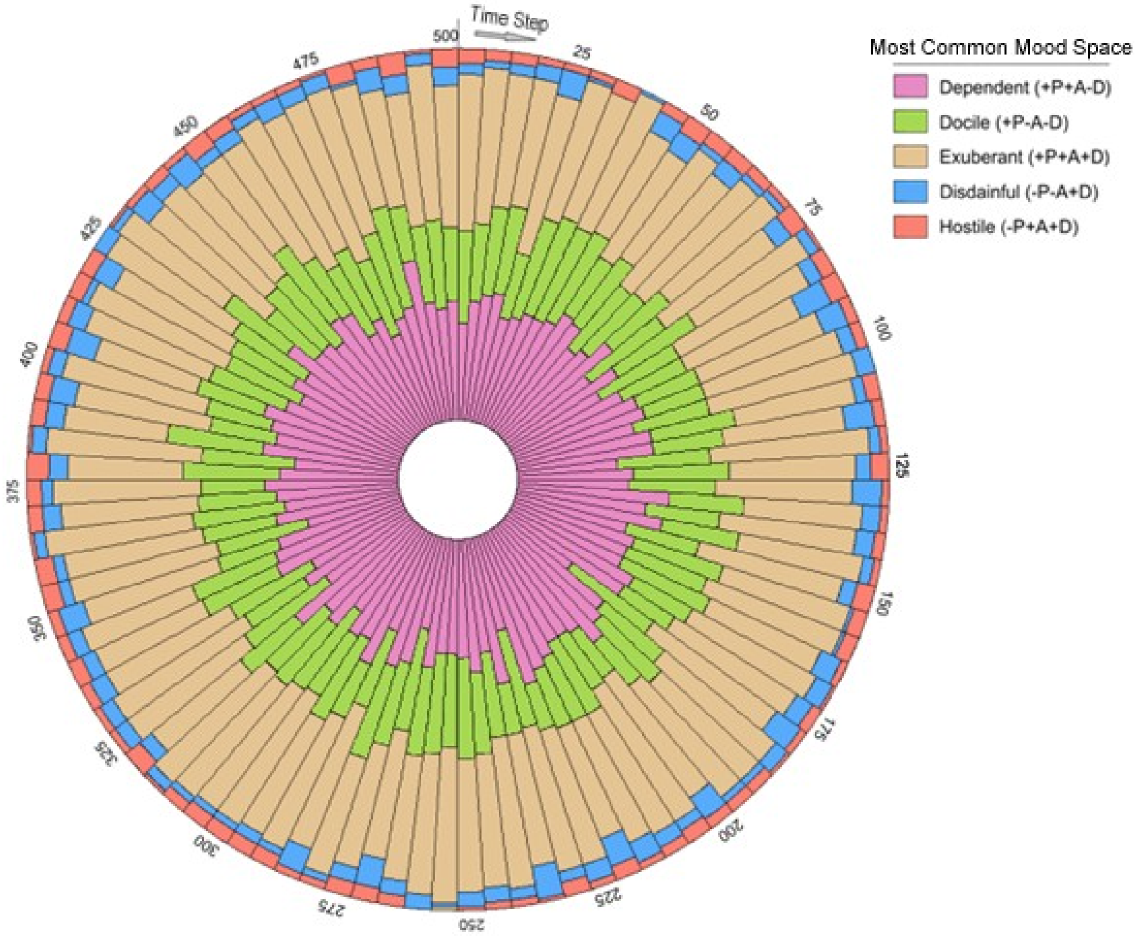

Figure 10.8: Ring Histogram of the Most Common Average Mood Space in the Simulations

agents sense a lack of control during a sequence of social interactions. Agents will relinquish control in a social network when they have become more inclined to be less selfish in favor of cooperation. The overall C-leaders often exhibited the highest level of dependent mood space at the end of school or work interaction exchanges. The last two mood spacings comprise a small portion of each simulation run in the ring diagram, but disdainful and hostile moods signify the presence of uncooperative behaviors. Interesting, context preservation is a requirement for these mood spacings, but in a negative sense. Agents that are disdainful or hostile are displeased with their neighbours' continual level of selfishness so they resort to antisocial behavior to gain a degree of control within the grouping.

10.7 Conclusions

Spatial agent-based modeling will be viewed as unnecessarily complicated by many of the practitioners who are more comfortable with the traditional approach of the qualitative analysis of social relationality. Yet, the most complicated element in designing and implementing an agent-based system is representing the variable, non-linear decision-making of the citizens. While the unwritten credo of 'Keep It Simple Stupid" should be paramount in the development of any model, there comes a point when a complicated framework is necessary to expand the applicability of the system. Start with the simple view of a community as a network of social interactions consisting of people going about their daily lives. Each person is an individual who makes decisions according to his appraisal of what is beneficial both for himself and the community as a whole. This autonomy of human behaviours is crucial for the self-organization of the entire socio-geographic community so the actual foundation of bottom-up decision-making is the individual. Complexity theory provides a context for simulating the self-organized emergence of the processes that define and sustain a community, and an agent-based model is appropriate formalization of this complex adaptive system.

The subject of this paper is a spatial agent-based systems model developed to simulate emergent cooperation and leadership from the nonlinear social interactions of mobile agents in a socio-geographic environment. The architecture is a tightly-coupled framework of functionally linked components that model spatial mobility, social communication, affective state, labour market dynamics, and self-organizing leadership. The complexity in the decision-making and the behaviors of the agents is captured by the bottom-up simulation of individuals as they participate in the social interactions of their daily activities. A benchmark set of simulation runs supports the common-sense expectations that a reward received from a social interaction sets an agent in a positive affective state, and the relationality required for a form of steady state cooperation is directly linked to context preservation of the interaction neighbourhoods.

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Part III: Discussion and Conclusions

11.0 Introduction

A human geography perspective on social relationality requires an understanding of complexity in both decision-making and the localized consequences of interpersonal interactions. The dynamics of social relationality reflect the fact that a community is a complex human system, consisting of many spatially and temporally varied processes directed by the sometimes stochastic and unpredictable decisions and behaviours of individuals. This research has produced a formalization that models a community as a complex adaptive system of social relationality by representing the individuals, defining the relationality among them, and identifying the spaces in which they act and are related.

11.1 Summary of the Research

The model developed in this work is a spatially explicit agent-based model that simulates the dynamics of social interactions with a set of generic components that model psychological states, multi-person social interactions, labour market dynamics, and emergent leadership.

The basic framework for simulating multi-agent social interactions is presented in paper one as a spatially explicit agent-based model that simulates N-Person's Prisoner's Dilemma games, where the configuration of the spatially defined neighbourhoods is conditioned on the activities and mobility of citizen agents. Simulation runs explored the influence of mobility and neighbourhood size on the self-organization of the modeled community. One set of simulations demonstrated that the movement and action choices of mobile agents led to a common emergent pattern of smaller clusters of cooperators and defectors that varied in size and locations. A second set of simulations with fixed agents investigated the role of context preservation and neighbourhood depth, and found that social interactions among familiar citizens led to increased instances of spatial groupings comprised predominately of cooperators.

The second paper modifies the N-Person Prisoner's Dilemma by endowing agents with affective states in their anticipation and response to the outcomes of social interactions. The hierarchical structure of the layered Personality-Mood-Emotion model of affect calculates the intensity of the triggered emotions from the outcomes of N-Person Prisoner's Dilemma events and adjusts the intensities further relative to temporal mood state and personality. The most common average emotion of agents who received a payoff was joy while those with a penalty experienced either reproach or anger. For agents that remain in the same neighbourhood for multiple time steps, the sense of social bonding that developed among them was a condition for the emergence of admiration as the most common average emotion and dependence as the most common average temporal mood. In a grouping of socially bonded individuals, neighbours relinquish their self control and cooperate for the benefit of the social network. The long-term affect of personality relates to the degree of neuroticism and extraversion in the agents, and plays a determining role in the decision of some agents to avoid participation in social interaction events.

The third paper presents a spatial labour market game with preferential partnership matching and Iterative Prisoner's Dilemma worker-employer exchanges.

Simulation runs investigated the influence of distance between employees and firms on the emergence of preferential partnerships, labour market participation rates, and action choices. The initial simulations were used to both calibrate the model and compare the resultant patterns of employee-firm partnerships to the findings from the original research of Tesfatsion (1997). With low to medium distance costs and low non-employment payments, the need for potential employees to travel to firms to submit job offers had a negligible effect on the emergent structure of the labour market. As with Tesfatsion (1997), potential employees will direct interactions to the firms with the highest associated expected payoff and firms will offer jobs to the potential employees highest on their waitlist. As the non-employment payment was raised from low to high, increased instances of non-participation were spatially dispersed throughout the labour market. The likelihood that the latched firm-employee pairs would engage in Cooperation-Cooperation action choice was slightly increased at the higher non-employment payment settings, but the social welfare values are subsequently deflated, producing a less cooperative environment. When the distance cost was set at medium and high thresholds, the cumulative distance penalty had a stronger negative influence on the decisions of potential employees to participate in the labour market. The significance of space was evident in the results from a high non-employment payment-high distance cost simulation. The social network of firm-employee relationships was reorganized into a smaller group of the most distant firms latched to the geographically closest employees.

The model in paper 4 for self-organizing leadership presents a framework for simulating the structure of social positioning in a community environment. The framework entangles administrative and adaptive leadership in an environment where individuals can introduce and enable conditions that catalyze the emergence of a leadership structure. Leadership emerges from the space between individuals from the tensions in the decisions of agents during N-Person Prisoner's Dilemma game play and the enabling actions of administrative and cooperation leaders. Context preservation is essential to the sustainability of cooperation and trust among the agents. The mobility dynamics of the unsatisfied agents are determined by the locations of tagged individuals in a "well-connected" community.

Paper five presents a comprehensive model designed to simulate social relationality as a result of the emergence of cooperation and leadership in a community. The framework of the model consists of the integration of the components of community development presented in the previous papers. Mobility actions of the agents depend on expected payoffs, and everyday activities are modeled as affective multiple person social exchanges or dyadic labour market transactions. In a benchmark simulation, common sense expectations were confirmed with the finding that agents most often experienced a positive affective state after they have received a payoff from a social interaction event. Also, the context preservation of the interaction neighbourhood lead to a sense of bonding between the agents that moved the dynamics towards a form of steady state cooperation. For the school and work events where context preservation was deliberately introduced, the percentage of cooperation increased due to the temporal constancy of the agent grouping. However, the single time step activity neighbourhoods had a blending of cooperators and defectors, with defection being the best action choice of the agents.

An interesting result was the emergence of multiple cooperation leaders at different preserved neighbourhoods. The longer these successful agents remained in place, the stronger the cooperation grew, because unsatisified agents traveled to their location to interact with a known cooperator. The longer an agent remained the cooperation leader, the greater the social mimicry of his action strategy, which increases the probability of greater instances of cooperation at later time steps. The cooperation leaders often experienced the highest intensity of a ***dependent*** (+P+A-D) mood space. The negativity of dominance as a mood trait indicates that these leaders had little interest in controlling social interactions for personal gain and exhibit recurrent altruistic behaviours instead. Familiarity and trust were minimal at the unpreserved neighbourhoods, and these were determined to be a primary condition for the emergence of the defection leader. The defection leader had the good fortune of being the highest paid defector in a neighbourhood for a single time step activity. From being rewarded with the largest payoff, the defection leader also experienced the highest exuberant mood space intensity.

11.2 Achievements of the Research

The following are the most significant findings of this research:

- *Affective decision making affords a more realistic approximation of human social interactions.*

  Many agent-based models of human systems simulate the behaviors of individuals with deterministic schemas and simple rulebases. Representing agents as objects that choose a course of action only according to a utility level ignores the complexity and autonomy of their behaviours. Emergent cooperation and leadership in a community environment are more realistically modeled with affective agents, because the developing sense of community influences their participation in and response to the dynamics of their social interactions. Agents with a personality will also appeal to researchers of a trait theory of leadership, because certain OCEAN factors sway the participation and responses of citizens in the everyday activities. Participation in social interactions is essential for the sustainability of relationality in the social network, which conditions the emergence of the cooperation and defection leadership structure in the community.

- *Space is an important element in labour market dynamics that should not be ignored.*

The standard economic models of labour market dynamics, such as the original Trade Network Game, often have no mechanism to incorporate space in the analysis. It is recognized in this research that many of the traditional models are generic abstractions so the dismissal of space is a methodological decision to simplify the architecture of system. However, the counter argument can be made that a modeling framework that ignores space is itself theoretically suspect. Space (e.g. location of firms and employees, shipping destinations, etc,) and spatial mobility (labour market commuting flows, distance costs) are elements in the processes of agent matching and social interactions that also direct the emergence of cooperation in the social environment. The methodology of the spatial labour market game incorporates space into the original Trade Network Game formalization and provides a framework that accommodates the needs of both economists and geographers.

The ability of agent-based modeling to simulate an economic environment in a more realistic and plausible manner is beneficial to both fields of research.

- *Emergent cooperation and leadership are directly correlated to context preservation.*

  Relationality depends on the familiarity and confidence that agents have in the decisions and action choices of their neighbours. In preserved neighbourhoods, agents continually interact with the same set of individuals for a set period of time, which enables each agent to make a temporal evaluation of the behavorial patterns in his social interactions. The memories and learning abilities of the individuals set the condition that selfish actions will be remembered and reciprocally acted upon. As the instances of cooperation increase, the agents begin to admire the selfless behaviors of their neighbours and cooperate in response. The agent in the preserved neighbourhood that initiates and promotes cooperation directs the social group towards a consensus decision, which makes this individual a localized cooperative leader. As the lowest rewarded citizens adopt his action strategy, the possibility of a form of steady state cooperation in the neighbourhood increases, and this improves the social position of the localized cooperation leader in the community.

- *The complex adaptive systems approach is essential in the modeling of the processes of community development.*

  With social relationality as a complex process, higher-level order can arise in the social networks as enabled individuals communicate and disseminate knowledge throughout the environment. The social exchanges between agents are non-linear in nature, because of the repeated feedback through the emergent structures within the social network. Many of the standard approaches to social relationality are implemented in a top-down framework, and lack the appropriate methodology to include decision-making at an individual level. This factor is central to the criticism that some contemporary researchers attach to the conventional methods as being inappropriate to handle the interaction dynamics in a community. In this research, the processes of social relationality are modeled as a complex adaptive system, where the stochastic dynamics of the social exchanges between the individuals lead to the emergence of structural changes in the socio-geographic network. Guided by the idea that a community could be modeled as a complex adaptive system, the spatial agent-based approach of this research may supplement the traditional theories of community development, which tend to ignore the processes by which a community organization interacts to reach or fails to reach a consensus.

11.3 Future Work

This research has contributed to the fields of computational sociology and human geography by demonstrating the advantages of spatial agent-based modeling in simulating the dynamics of a complex human system. However, there are still areas that need to be investigated and some aspects of this model can be further refined. They are summarized as follows:

- *Holistic Agent-based Modeling of Community Development.*

  In its current form, the framework of this model is based only on the processes of social relationality. Further development of the model as a system that can simulate the broad range of dynamics associated with community development requires several extensions. At the very least, components that simulate relevant aspects of the culture, the natural environment, the governance structure and the economy would have to be included in the model. With a labour market component already developed, the integration of an economic model is a natural start. An interesting possibility is the agent-based modeling approach of a simple Luhmann economy proposed by Fleischmann (2005). A Luhmann economy is based on the proposition that an economy functions as a subsystem of society and that economic development is an evolutionary process of the exchange of goods between agents. The manner in which agents access these goods produces an ownership code that emphasizes that it is better to own the good than desire it. The economic system starts from and produces an inequality in goods in order to continue and uses agent interactions to evolve towards a near equilibrium balance between the supply and demand for the good. The essential elements are the stocks and flows, and the demand for goods results from the observed differences in ownership of scarce goods. In this approach, a Luhmann economy could consider as goods the labour services that individuals offers to the system and that firms purchase in the form of jobs. Another possibility is the comprehensive model of an evolving economic system developed by

Straatman et al. (2008), which uses artificial chemistry to simulate the production system of an economy. The modeling environment consists of social networks, agents, products, and technology and changes in the economy can occur when agents expand their interaction network, buy and sell commodities, or adopt new technologies. The integration of components of the model presented in this thesis and the model of Straatman et al. (2008) would benefit both formalizations. For example, the selection of trading partners in the artificial chemistry economy could be improved with the preferential partnership matching mechanism of the spatial labour market game, and this could aid in the determination of market price. An economy is an essential component of a model of community development, and the approach of Straatman et al. (2008) is an innovative way of including technology and natural resources into the modeling environment. These two elements are essential for directing development plans in rural communities, where a common proposal for improving economic conditions is the introduction of new technology and the harvesting of natural resources.

- *Modeling fuzziness in the affective states and action choices of the agents (Paper 1 Future Research).*

  The classical definition of Prisoner's Dilemma is a simplistic representation of cooperation, one only allows a boolean assignment to two cooperation classes. Cooperation should be measured on a continuous state space that varies at each time step according to the attitudes of the agents. As a further model revision, a Mamdani fuzzy inference system can provide a flexible base for developing a modeling component that assigns fuzzy memberships to an agent for both cooperation and defection. The purpose of the fuzzy inference system is to model agent decisions to cooperate by considering both the standard Prisoner's Dilemma probability approach and the affect of the emotional state of the agent. Using a set of fuzzy membership functions each agent is assigned a degree of membership in both classes to produce a continuum of cooperation in the modeling environment. A fuzzy rulebase will model the decision choices of the agents by inferring their willingness to cooperate as a consequence of an agent's emotional state and payoff from a social interaction event. The willingness to cooperate is implemented as a fuzzy cooperation value, which ranges from 0 to 1. This alternative to the Boolean dichotomy of cooperation and defection would enable an agent to exhibit a more believable and varying degree of cooperation throughout the simulation.

11.4 Comments on the Research Experience

I am at a point in my PhD. research where I have started to reflect on my mindset as a geographer, and the question that constantly arises is "Do I have a better understanding of geographic human systems?" To answer that question, I have to go back to my previous life as a spatial analyst. Educated and trained in the theories of Geographic Information Sciences (GIS), my default approach to analyzing spatial phenomena was to apply some form of optimization or statistics to identify patterns in the data, investigate spatial dependencies, develop prediction models, etc. I looked at space with linear vision and never truly considered the issues with this perspective. I could fit a line through any of the datasets I studied, and would address the associated error in the usual statistical manner of confidence intervals. However, the inability of the methodologies in my GIS repertoire to incorporate time into the analysis always bothered me, but, like many spatial analysts, I accepted it as standard operating practice. Things changed when I was tasked with mapping a time series of demographic data, or at least what the client thought was a time series. The purpose of the project was produce chloropleth maps of population changes in communities over three Statistics Canada census releases (1996, 2001, and 2006) as a means of visually identifying growth areas and regions in decline. Each table of population counts for a census year is theoretically atemporal, because the data represents a snapshot of the sampled population on the day that the census survey was administered. A population change map tells nothing of the reasons why population has increased or decreased, and disregards the demographic dynamics between the census years. The more I thought about it, the more I realized that population change is due to the decisions, actions, and health status of the individual people in the communities.

This was an epiphany, because it was the first time that I considered studying the micro-scale dynamics of a geographic system, and, even more challenging, the dynamics of a human system. Also, the formalization of a human system from a quantitative GIS approach is a contrast with the qualitative perspectives of human geography so my initial research thought was to devise a methodology that integrated both approaches. I began with the common view of a human system as a community, a grouping of people in a spatially defined region such as a city or town, and thought that a set of rules that handle the qualitative aspects of human interactions could be the basis for a model of a community. This belief failed miserably, because it ignored the complexity of the processes of the human system. I needed the complexity perspective of an individual-based model of a community, and found what I was looking for in the theory of complex adaptive systems.

The focus of my research then became the development and implementation of a model of a community as a complex adaptive system that models the interactions and behaviours between people within a spatial confluence region. Spatial agent-based modeling was the natural choice as a computational approach to understanding a complex adaptive system, a decision which was further supported by the fact that agent-based modeling was becoming increasing common in human geography literature. Further, an agent-based modeling approach is ideal, because complex macro-level phenomena can be studied as emerging by a process of self-organization of the macro-level structure of the system from the micro-level behaviours of individuals.

The challenging task in the development stage of the model was representing the processes of interactions between individuals. I spent considerable time reviewing agent-based models in journals dedicated to sociology, psychology, economics, and robotic engineering in addition to the studies utilizing spatial agent-based models. It was the merger of the theories from these different research disciplines that resulted in the formalization of the model presented in this thesis.

I'll conclude this commentary by returning to the question about my understanding of a human system. The personal and professional benefits of this research are threefold. First, I can confidently state that my formal knowledge of the processes of a human system has improved considerably, but I have only scratched the surface when it comes to fully understanding all aspects of a human system. The true benefit is that it has made me keenly aware of the complexity of the social interactions that often drive a human system. The theory and findings of this thesis add to the field of human geography, but there are many avenues of research to pursue in the future. Secondly, I have witnessed my transformation from a spatial analyst to a spatial modeler, and to some degree, a human geographer. I never envisioned that I would abandon the statistical methodologies of GIS for the nonlinear stochastic dynamics of agent-based models of social, economic, and spatial phenomena. However, any model of a human system has to be as true as possible to the real world social environment that it is intended to represent, and this is achieved with an individual based-approach as presented in this thesis. Lastly, the epistemological advances of complex adaptive systems approaches to socio-geographic research must be mentioned. For example, any of the theoretical issues of the traditional economic geography, such as individual rational choice can be addressed with a complex adaptive system approach that simulates the behaviours of economic agents in space. As proposed by Schenk (2007), this could be an alternative framework of a relational view of economic geography. At the very least, I hope that any researcher who reads this thesis or any of the contributing papers will consider it an endorsement of interjecting tensions into their standard mindset to expand their knowledge of human systems.

11.5 References Part III

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12.0 Appendix I: Rules for Basic Emotions

A.1 For all emotions in the rule-based model, the following notations are applicable: $D_{(p,e,t)}$ is the desirability that agent p assigns to the outcome of an NPPD event e at time *t*, M_t is the temporal mood state, P_n is the neuroticism value in the OCEAN personality schema, N_t is the payoff received by agent p at time t, S_{t-1} is the action state (C: cooperation or D: defection) of the agent at time *t-1,* $Cp(e, S_{t-1})$ is the percentage of cooperators in the neighbourhood of agent e, I_E is the emotional intensity, I_M is the mood-emotional intensity, and I_{PME} is the combined affective intensity.

Rules for Joy: Joy = $\boldsymbol{f}(D_{(p,e,t)}, M_t, P_n)$,

$D_{(p,e,t)} = \boldsymbol{f}(N_t, S_{t-1})$

If S_{t-1} = C and $N_t > 0$ then
  set $I_E = N_t / P_{MaxC}$, where P_{MaxC} is the highest payoff that a cooperator can receive from the payoff function
Else If S_{t-1} = D and $N_t > 0$ then
  set $I_E = N_t / P_{MaxD}$, where P_{MaxD} is the highest payoff that a defector can receive from the payoff function
Else
  set $I_E = 0$
End If

If $M_t \equiv$ PAD $\equiv$ Positive Mood state then
  set $I_M = I_E + x$, where $x \in [0.001,0.05]$ is a uniform random value
Else If $M_t \equiv$ PAD $\equiv$ Negative Mood state then
  set $I_M = I_E - x$
End If

If $I_M \approx 0$ then
  If $P_n \approx 1$ then
   set $I_{PME} = I_M - y$, where $y \in [0.001,0.05]$ is a uniform random value to a minimum of 0
  Else If $P_n \approx -1$ then
   set $I_{PME} = I_M + y$
  End If
   set $I_{Joy} = I_{PME}$
Else
  set $I_{Joy} = I_M$
End If

Rules for Distress: Distress = $\boldsymbol{f}(D_{(p,e,t)}, M_t, P_n)$,

$D_{(p,e,t)} = \boldsymbol{f}(N_t, S_{t-1})$

If $S_{t-1} = C$ and $N_t < 0$ then
set $I_E = N_t / P_{MinC}$, where P_{MinC} is the lowest payoff that a cooperator can receive from the payoff function
Else If $S_{t-1} = D$ and $N_t < 0$ then
set $I_E = N_t / P_{MinD}$, where P_{MinD} is the lowest payoff that a defector can receive from the payoff function
Else
set $I_E = 0$
End If

If $M_t \equiv PAD \equiv$ Positive Mood state then
set $I_M = I_E - x$, where $x \in [0.001, 0.05]$ is a uniform random value
Else If $M_t \equiv PAD \equiv$ Negative Mood state then
set $I_M = I_E + x$
End If

If $I_M \approx 0$ then
If $P_n \approx 1$ then
set $I_{PME} = I_M + y$, where $y \in [0.001, 0.05]$ is a uniform random value
Else If $P_n \approx -1$ then
set $I_{PME} = I_M - y$, to a minimum of 0
End If
set $I_{Distress} = I_{PME}$
Else
set $I_{Distress} = I_{ME}$
End If

Rules for Hope: Hope = $\boldsymbol{f}(L_{S_{t-1}}, D_{(p,e,t)}, M_t, P_n)$,
where $L_{S_{t-1}}$ is the likelihood of receiving a positive payoff $\boldsymbol{p}$ from the action state of the agent at time *t-1*

From the payoff functions, $L_{S_{t-1}} \propto Cp_{(e, S_{t-1})}$ when $Cp_{(e, S_{t-1})} > Cp_z$, where Cp_z is the condition of $Cp_{(e, S_{t-1})}$ that will derive a prospect payoff $\boldsymbol{p} = 0$

If $Cp_{(e, S_{t-1})} > Cp_z$ Then
set $L_{S_{t-1}} = (Cp_{(e, S_{t-1})} - Cp_z) / (1 - Cp_z)$
Else
set $L_{S_{t-1}} = 0$
End If

$D_{(p,e,t)} = \boldsymbol{f}(L_{S_{t-1}}, \boldsymbol{p}_{t-1})$, where $\boldsymbol{p}_{t-1}$ is the one step memory payoff at time *t-1*

Note: Hope is increased with a history of negative payoffs

If $\boldsymbol{p}_{t-1} < 0$ then
 set $D_{(p,e,t)} = \boldsymbol{p}_{t-1} / P_{Min}$,where P_{Min} is the lowest payoff that an agent with action state S_{t-1} can receive
Else
 set $D_{(p,e,t)} = 0$
End If

If $L_{S_{t-1}} \geq 0.75$ then
 If $D_{(p,e,t)} > 0.8$ then
  set $I_E = r_h$, where $r_h \in [0.8,1]$ is a uniform random value
 Else If $D_{(p,e,t)} \geq 0.5$ and $D_{(p,e,t)} \leq 0.8$ then
  set $I_E = r_h$, where $r_h \in [0.6,0.8]$ is a uniform random value
 Else
  set $I_E = r_h$, where $r_h \in [0.3,0.6]$ is a uniform random value
 End If
Else If $L_{S_{t-1}} \geq 0.5$ and $L_{S_{t-1}} < 0.8$ then
 If $D_{(p,e,t)} > 0.8$ then
  set $I_E = r_h$, where $r_h \in [0.7,0.8]$ is a uniform random value
 Else If $D_{(p,e,t)} \geq 0.5$ and $D_{(p,e,t)} \leq 0.8$ then
  set $I_E = r_h$, where $r_h \in [0.4,0.7]$ is a uniform random value
 Else
  set $I_E = r_h$, where $r_h \in [0.25,0.4]$ is a uniform random value
 End If
Else
 set $I_E = r_h$, where $r_h \in [0.01, 0.25]$ is a uniform random value
End If

If $M_t \equiv PAD \equiv$ Positive Mood state then
 set $I_M = I_E + x$, where $x \in [0.001,0.05]$ is a uniform random value
Else If $M_t \equiv PAD \equiv$ Negative Mood state then
 set $I_M = I_E - x$
End If

If $I_M \approx 0$ then
 If $P_n \approx 1$ then
  set $I_{PME} = I_M - y$, where $y \in [0.001,0.05]$ is a uniform random value to a minimum of 0
 Else If $P_n \approx -1$ then
  set $I_{PME} = I_M + y$
 End If
set $I_{Hope} = I_{PME}$
Else
 set $I_{Hope} = I_M$

End If

Rules for Fear: Fear = $\boldsymbol{f}$ ($L_{S_{t-1}}$, M_t, P_n),

where $L_{S_{t-1}}$ is the likelihood of receiving a negative payoff $\boldsymbol{p}$ from the action state (C or D) of the agent at time *t-1*

From the payoff functions, $L_{S_{t-1}} \propto Cp_{(e, S_{t-1})}$ when $Cp_{(e, S_{t-1})} > Cp_z$, where Cp_z is the condition of $Cp_{(e, S_{t-1})}$ that will derive a prospect payoff $\boldsymbol{p} = 0$

If $Cp_{(e, S_{t-1})} < Cp_z$ Then
 set $L_{S_{t-1}} = (Cp_z - Cp_{(e, S_{t-1})}) / Cp_z$
Else
 set $L_{S_{t-1}} = 0$
End If

$I_E \propto L_{S_{t-1}}$ but subjected to a random perturbance to model nonlinearities
$\therefore I_E \approx (L_{S_{t-1}} \pm r_p)$, where $r_p \in [0.001, 0.1]$

If $M_t \equiv PAD \equiv$ Positive Mood state then
  set $I_{ME} = I_E - x$, where $x \in [0.001,0.05]$ is a uniform random value
Else If $M_t \equiv PAD \equiv$ Negative Mood state then
  set $I_{ME} = I_E + x$
End If

If $I_M \approx 0$ then
  If $P_n \approx 1$ then
   set $I_{PME} = I_M + y$, where $y \in [0.001,0.05]$ is a uniform random value
  Else If $P_n \approx -1$ then
   set $I_{PME} = I_M - y$, where $y \in [0.001,0.05]$ is a uniform random value to a minimum of 0
  End If
   set $I_{Fear} = I_{PME}$
Else
  set $I_{Fear} = I_M$
End If

Rules for Relief: Relief = $\boldsymbol{f}(I_{Fear}, N_t, M_t, P_n)$

$I_E \propto I_{Fear}$

If $N_t > 0$ then
  set $I_E = I_{Fear} + r_i$, where $r_i \in [0.001,0.01]$ is a uniform random value

Else
 set $I_E = 0$
End If

If $M_t \equiv PAD \equiv$ Positive Mood state then
 set $I_M = I_E + x$, where $x \in [0.001,0.05]$ is a uniform random value
Else If $M_t \equiv PAD \equiv$ Negative Mood state then
 set $I_M = I_E - x$
End If

If $I_M \approx 0$ then
 If $P_n \approx 1$ then
  set $I_{PME} = I_M - y$, where $y \in [0.001,0.05]$ is a uniform random value to a minimum of 0
 Else If $P_n \approx -1$ then
  set $I_{PME} = I_M + y$, where $y \in [0.001,0.05]$ is a uniform random value
 End If
  set $I_{Relief} = I_{PME}$
Else
 set $I_{Relief} = I_M$
End If

Rules for Admiration: Admiration = $\boldsymbol{f}$(Tcn_e, $Cp_{(e, S_{t-1})}$, N_t, M_t, P_n), where Tcn_e is the neighbourhood strength or temporal constancy of the neighbours of agent e indicated as the number of continuous time steps that e interacts with the same neighbours

‘A sense of familiarity from a minimum of three interactions with the same agents

If ($Tcn_e \geq 3$) Then
 If (S_{t-1} = C and $Cp_{(e, S_{t-1})} \geq 0.60$) then
  set $I_E = N_t / P_{MaxC}$, where P_{MaxC} is the highest payoff that a cooperator can receive from the payoff function
 Else
  set $I_E = 0$
 End If

  If $M_t \equiv PAD \equiv$ Positive Mood state then
   set $I_M = I_E + x$, where $x \in [0.001,0.05]$ is a uniform random value
  Else If $M_t \equiv PAD \equiv$ Negative Mood state then
   set $I_M = I_E - x$
  End If

  If $I_M \approx 0$ then
   If $P_n \approx 1$ then

set $I_{PME} = I_M - y$, where $y \in [0.001,0.05]$ to a minimum of 0
Else If $P_n \approx -1$ then
set $I_{PME} = I_M + y$, where $y \in [0.001,0.05]$ is a uniform random value
End If
set $I_{Admiration} = I_{PME}$
Else
set $I_{Admiration} = I_M$
End If
Else
set $I_{Admiration} = 0$
End IF

Rules for Reproach: Reproach = ***f***(Tcn_e, $Cp(e, S_{t-1})$, N_t, M_t, P_n), where Tcn_e is the neighbourhood strength or temporal constancy of the neighbours of agent e indicated as the number of continuous time steps that e interacts with the same neighbours

‘A sense of familiarity from a minimum of three interactions with the same agents

If ($Tcn_e \geq 3$) Then
If (S_{t-1} = D and $Cp(e, S_{t-1}) \geq 0.60$) then
set $I_E = N_t / P_{MaxD}$, where P_{MaxD} is the highest payoff that a defector can receive from the payoff function
Else
set $I_E = 0$
End If

If $M_t \equiv PAD \equiv$ Positive Mood state then
set $I_M = I_E - x$, where $x \in [0.001,0.05]$ is a uniform random value
Else If $M_t \equiv PAD \equiv$ Negative Mood state then
set $I_M = I_E + x$
End If

If $I_M \approx 0$ then
If $P_n \approx 1$ then
set $I_{PME} = I_M + y$, where $y \in [0.001,0.05]$ is a uniform random value
Else If $P_n \approx -1$ then
set $I_{PME} = I_M - y$, where $y \in [0.001,0.05]$ to a minimum of 0
End If
set $I_{Reproach} = I_{PME}$
Else
set $I_{Reproach} = I_M$
End If
Else

set $I_{reproach} = 0$
End IF

Rules for Anger: Anger $= \boldsymbol{f}(Tcn_{e,} I_{Distress}, I_{Reproach})$, where Tcn_e is the neighbourhood strength or temporal constancy of the neighbours of agent e indicated as the number of continuous time steps that e interacts with the same neighbours

If (Tcn_e < 3) Then
'with less than 3 time steps, the agent is angered more by the distress of a negative payoff
set $I_{Anger} = (0.6* I_{Distress}) + (0.4 * I_{Reproach})$
Else
'with ≥ 3 time steps, the agent is angered more by the groupings action choices
set $I_{Anger} = (0.4* I_{Distress}) + (0.6 * I_{Reproach})$
End IF

13.0 Appendix II: Mood Adjustment

A.2 Consider that the PAD entries listed in Table 7.3 are the mood values for each emotion when I_e =1, where I_e is the intensity of activated emotion *e*. The adjusted PAD spacing for emotion e is dependent on its intensity:
With I_{e_i} is the intensity of emotion *i:*

$P_{e_i} = I_{e_i} P_e$,where P_e is the maximum pleasure value for emotion *i* from Table 7.3
$A_{e_i} = I_{e_i} A_e$,where A_e is the maximum arousal value for emotion *i*
$D_{e_i} = I_{e_i} D_e$,where D_e is the maximum dominance value for emotion *i*

With N as the number of emotions e with $I_e > 0$, the average PAD spacing is computed as:

$$\overline{P_e} = \sum_i^n P_{e_i} / \text{N, where n=1,...N}$$

$$\overline{A_e} = \sum_i^n A_{e_i} / \text{N, where n=1,...N}$$

$$\overline{D_e} = \sum_i^n D_{e_i} / \text{N, where n=1,...N}$$

The resultant average mood state then translates to:

$$\overline{PAD} \equiv \overline{P_e}\, \overline{A_e}\, \overline{D_e}$$

The final step in the mood adjustment is the setting of the temporal mood state M_t, which is a three-step memory weighted summation of the average mood states. Weighted summation allows the weights to be linearly decayed so that the effects of the average mood state decreases with each time step. Formally, M_t adjusts each of the average PAD elements:

$$M_{P_t} = \sum_i^3 W_i \overline{P_{e_i}}$$

$$M_{A_t} = \sum_i^3 W_i \overline{A_{e_i}}$$

$$M_{D_t} = i\sum_i^3 W_i \overline{D_{e_i}}$$

,where W_I=1

$\therefore M_t \equiv M_{P_t} M_{A_t} M_{D_t}$