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A spatial agent-based model of a congestion game: evolutionary game theory in space

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Abstract This paper develops a theoretical framework to analyze traffic congestion from a micro-behavioral foundation perspective. It extends the evolution of an n-person prisoner's dilemma within actual geographical space, integrating an agent-based model with GIS, in conflicting spatial interactions that ultimately lead to the decline of cooperation. The spatial agent-based model captures the response strategies of autonomous individuals in a landscape that contextualizes both the natural and the built environment. The result suggests that the loss of context preservation could lead to the extinction of cooperation, the opposite of the earlier findings. This theoretical framework thus serves as a basis for the analysis of collective strategic decisions about the use of a common resource from a game theoretical perspective.

JEL Classification C63 · C73

1 Introduction

Game theory has long been applied to explain the competitive/cooperative behaviors of agents based on their strategic interactions. It is the study of how people behave when considering how others might respond to such behavior. In particular, the paradox of prisoner's dilemma has been extensively examined in the field of sociology and biology as a metaphor of a simple and interesting situation occurring when actions

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of rational individuals pursuing their self-interest lead to a worse outcome as a whole than if they had cooperated. One classic example of the prisoner's dilemma is a story of two arrested suspects. Interrogated separately by the police, each suspect must decide to confess (and blame the other) or keep silent. If the other confesses, one would be better off doing the same to avoid harsh punishment. On the other hand, if the other stays silent, one would be better off confessing to gain favorable treatment. When both confess, however, the outcome is worse for both than if they both keep silent.

Further, the prisoner's dilemma also provides a basis for the analysis of the governing of common-pool resource usage, also known as collective action problems—situations when no contributions are made by rational self-interested individuals toward the production of common goods. The common-pool resource includes not only natural goods but also man-made ones such as irrigation systems, infrastructure, and road networks, which often face a problem of congestion or overuse when not well-managed (Ostrom 1990). Ostrom (2000) discusses experimental and empirical evidence of various design regimes of self-organization and governance to achieve the benefits of collective action. In her view, contextual factors, such as communication, trust, governance rules, and social norms, play a key role in promoting or discouraging cooperation, which in turn affects the rate of contribution to public goods. One important question arises, however, regarding how these contextual factors affect and maintain cooperation through time. Taking an evolutionary theory approach, Ostorm argued, is the essential first step to address how context matters.

Most of the literature, nonetheless, often focuses on the evolution of cooperation of either two- or multiple-player iterated games, without taking into consideration the contextual space on which agents locate, migrate, and interact [e.g., see Schelling (1971), Axelrod (1984), Nowak and May (1992), and Cohen et al. (1999)]. Little has been done to examine how the role of spatial context affects how agents adapt and interact in a prisoner's dilemma situation.

This paper aims to fill in this gap. It develops a game theory analytical framework with visual representation tool. The situation on which the analysis focuses is traffic congestion in public road networks, which is one of many examples of common-pool resource problems. The aim is to examine traffic congestion from the micro-behavioral, game theoretical perspective. The basic concept of the congestion game (Levinson 2005) serves as a basis for the analysis of strategic interactions among agents undertaken in this study. As more and more motorists enter the road, they have direct impacts not only on their own travel time but also on the overall travel time of all motorists in the system. In addition, local interactions among motorists—such as overtaking or yielding—are a contributing factor to traffic congestion (Levinson 2005).

However, this study has taken a rather different approach from the congestion game of Levinson (2005) by adding adaptive behavior and integrating a spatial context, which is absence in the congestion game, into the model. The model explicitly allows for vehicle movement and spatial interactions among agents within actual geographical space in geographical information systems (GIS) as in Malleson (2011) and allows for agents' adaptive behavior as in Cohen et al. (1999). This spatial agent-based model captures the response strategies of autonomous individuals, while GIS contextualizes both the natural and built environments.

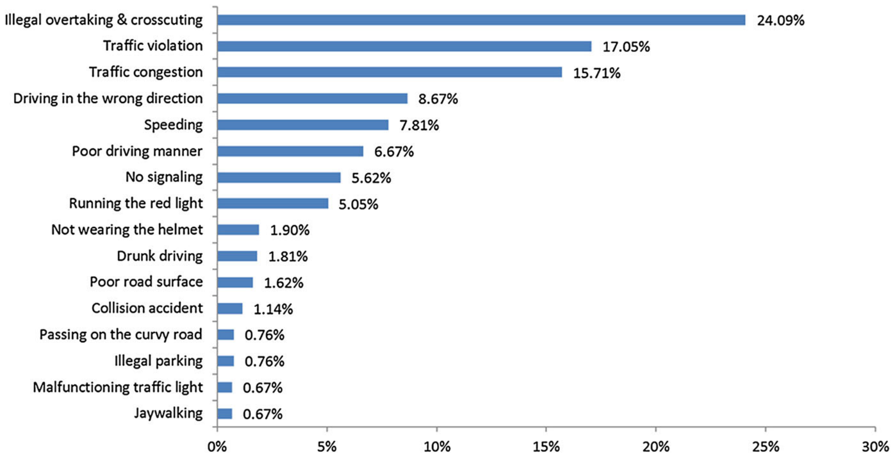

Fig. 1 Thai perception on traffic problems

To analyze such driving behaviors, we utilize empirical data of Bangkok. With over 600 new private vehicles on the road daily, Bangkok is one of the most congested cities in the world. During rush hours, for example, cars on the road in Bangkok can move merely at 10–15 km (6–10 mile) per hour on average and typically can stand still in the traffic for hours (Office of Transport and Traffic Policy and Planning 2013). With severely congested traffics come stresses and frustration for all motorists; consequently, confrontation and conflict between them over a precious space on the road seem unavoidable. According to a 2012 survey "Thais and Traffic Discipline" by National Institute of Development Administration, illegal overtaking and crosscutting were found to be the most common problem on the road perceived by Thais, followed by traffic violation and congestion (see Fig. 1). Clearly, the survey results suggest that negligent behaviors are recognized among Thais as a major traffic problem.

The focus of this study is an attempt to understand the effect of spatial context on agent's cooperative strategies and evaluate the collective impact of such interactions on congestion in terms of overall travel times. Specifically, while making their trips, drivers may choose to be responsible (obeying traffic regulations) or negligent (violating regulations). The main research question is, when agents are freely mobile on a spatial context so that their interacting neighbors are changing and not constant, whether cooperative behavior would collectively lead to a better social outcome, i.e., less traffic congestion in this analysis.

2 Literature review

2.1 Theoretical and empirical background

2.1.1 Evolutionary prisoner's dilemma

One aspect of game theory that has been extensively studied in economics and decision theory is the prisoner's dilemma. The classic example of the prisoner's dilemma

Table 1 Payoff matrix in a classical prisoner's dilemma

Player1	Player 2	
	Cooperate	Defect
Cooperate	R, R	S, T
Defect	T, S	P, P

comes from a story of two prisoners who face two choices of action: to remain silent (cooperate, C) or to testify against the other (defect, D). Without knowing each other's strategies, a prisoner must decide whether to confess or not to confess. In a generic form, the value for their judgment is presented in a payoff matrix given in Table 1.

Reward for mutual cooperation (R) is the payoff value if both players cooperate, while punishment for mutual defection (P) is the value if both players defect. Temptation to defect (T) and Sucker's payoff (S) are payoff values when a player defects alone and cooperates alone, respectively (Axelrod 1984). According to Axelrod (1984), what characterize the prisoner's dilemma are not the absolute values in the payoff matrix, but rather the rank ordering of the payoffs. These payoff values are such that $T > R > P > S$ to ensure that a player always has an incentive to defect since the payoff value is greater than when both cooperate. As a result, regardless of the other's action, both prisoners choose to defect, and they are worse off than if they both had cooperated. This classic example of the prisoner's dilemma precisely demonstrates how individual rationality could lead to a worse outcome for both players (Axelrod 1984).

Nonetheless, the shortcomings of the classical prisoner's dilemma stem from its simplicity. As discussed in Power (2009), since the prisoner's dilemma is intended to study only two-person interactions, it does not represent realistic interactions of individuals. In addition, it is assumed that there is no communication among players and no memory of the past interactions, which may lead to collaborative strategies. Furthermore, as players are assumed to be rational, both players will always choose to defect to maximize their utilities.

An extension of the classical prisoner's dilemma presented by Axelrod (1984) is known as evolutionary prisoner's dilemma (EPD). Like the classical prisoner's dilemma, communications among players are not possible in the EPD. Unlike the classical prisoner's dilemma, the EPD allows players to repeatedly choose strategies, or decision rules, based on their memory of previous encounters. Players' current actions are drawn only from their previous interactions with others; in other words, players are myopic decision makers. Evolutionary prisoner's dilemma is also applicable to the interaction with more than two players, as in classical game theory, in order to examine the collective behavior of social groups since strategies that work well with individuals may not be appropriate for group decisions.

Similar to the classical prisoner's dilemma, participants in the EPD play several consecutive games using the payoff matrix to accumulate points over the game period. The player with the higher score would be able to influence their opponents to cooperate. The payoff matrix for EPD is given in Table 2.

As players are allowed to play multiple games consecutively, their strategies specify agents' actions in any situations that may arise. There are four strategies possible, namely always cooperating (ALLC), Tit-for-Tat (TFT), Anti-Tit-for-Tat (ATFT), and

Table 2 Numerical example of a payoff matrix in evolutionary prisoner's dilemma

Player1	Player 2	
	Cooperate	Defect
Cooperate	3, 3	0, 5
Defect	5, 0	1, 1

always defecting (ALLD). ALLC is a strategy where an agent always cooperates, while an agent choosing an ALLD strategy always defects. Tit-for-Tat is a decision rule to cooperate in the first move and then do whatever the opponent does in the last encounter. In other words, if his opponent cooperates in this round, the player will cooperate in the next round. To put it in layman's terms, it means "if you are nice to me this time, I will be nice to you the next time we meet." Anti-Tit-for-Tat is simply the opposite of Tit-for-Tat.

Among these four strategies, Tit-for-Tat is found to be the best strategy because it gives the highest payoffs (Axelrod 1984; Nowak and May 1992; Cohen et al. 1999). As Power (2009) puts it, "altruism strategies tend to outperform greedy ones over the long run."

2.1.2 Evolutionary prisoner's dilemma in agent-based model

The notion of EPD has been applied to many studies using agent-based modeling [e.g., see Bazzan et al. (2002), Cohen et al. (1999) and Gulyás and Płatkowski (2004)]. The strategies in the EPD can be used to characterize agent relationships in the agent-based model. Similar to Cohen et al. (1999), the ABM in this study employs a decision rule for the agent using a "binary" strategy; the strategy may vary according to two factors: the probability of cooperating after the other cooperates (p) and the probability of cooperating after the other defects (q). Since on the first play, there is no history of previous encounters to draw upon, the probability of the agent cooperating in the first move (denoted as i) also needs to be specified. With these variations in (i, p, q) combinations, agents are restricted to one of these four types:

- $i = p = 1, q = 1$: always cooperating (ALLC),
- $i = p = 1, q = 0$: Tit-for-Tat (TFT),
- $i = p = 0, q = 1$: Anti-Tit-for-Tat (ATFT), and
- $i = p = 0, q = 0$: always defecting (ALLD).

At the beginning of the simulation, agents are divided equally into these four types of strategies. As the simulation proceeds, the fraction of agents in each combination (i, p, q) varies, but no new combination is created. These binary strategies are deterministic so that agents can immediately determine the payoffs of any numbers of plays. To illustrate this, a payoff matrix of four-move games is given in Table 3. The sum of four-move payoffs is shown in the parenthesis.

Generally, no best strategy exists independently of the strategy used by the other player. For example, ATFT and ALLD may do better than TFT and ALLC for player 1 when the opponent's (player 2's) strategy is ALLC, but it is the opposite when player

Table 3 Individual and four-move payoffs from interactions of all strategies. *Source*: Cohen et al. (1999)

Player1	Player 2			
	ALLC	TFT	ATFT	ALLD
ALLC	3333 (12)	3333 (12)	0000 (0)	0000 (0)
TFT	3333 (12)	3333(12)	0153 (9)	0111 (3)
ATFT	5555 (20)	5103 (9)	1313 (8)	1000 (1)
ALLD	5555 (20)	5111 (8)	1555 (16)	1111 (4)

Sum of payoffs is shown in parenthesis

2's strategy is TFT. In this sense, the variation in an opponent's strategy that a player encounters plays a crucial role in the emergence of cooperative regimes. Consequently, the system dynamics do not depend directly on global proportions of strategy types, but rather on an agent's adaptive behavior and on meetings of agents, i.e., who is interacting with whom, on a local scale.

Cohen et al. (1999) constructed a basic ABM model consists of 256 agents who are categorized equally into four strategies: ALLC, TFT, ATFT, and ALLD. Each agent is randomly allocated in a 16×16 grid in torus space so that agents of any strategies have an equal chance of meeting other agents with different strategies. In each iteration, each agent plays four games with his four adjacent neighbors in the north, east, south, and west—also known as a von Neumann neighborhood. In addition, the agents are adaptive, meaning that they change their strategies based on the interactions they have previously had with other agents. An agent first compares its score to its neighboring agents' scores during the current period. If the best score of the neighboring agents is higher than or equal to the agent's own score, the agent then adapts to that situation by imitating the strategy of the neighboring agent with the highest score. When its score is equal to the best score of its neighbors, the agent simply imitates its own strategy. At time 100, all agents adopt the Tit-for-Tat strategy, which supports the earlier findings that Tit-for-Tat is the best among the other three strategies.

2.1.3 Congestion game

Game theory has been applied in examining many transportation-related problems, for example, airport landing fees (Littlechild and Thompson 1977), truck weight limits (Hilderbrand et al. 1990), yielding and merging behavior (Liu et al. 2007), vehicle safety (Tay 2002), and traffic congestion (Levinson 2005; Zou and Levinson 2006). Traffic congestion, in particular, is profoundly a micro-behavioral problem. As Zou and Levinson (2006) put it, "congestion is a phenomena caused by multiple interacting individuals seeking to use a temporarily scarce resource in a short period of time." As such, congestion *emerges* as a result of the interaction of multiple players—or multiple vehicles—on the road.

Levinson (2005) sets up the game theory model for a congestion game using a simple two-player (or vehicle) interaction. A decision made by one traveler—such as departure time or vehicle maneuver—affects the journey delay and arrival times experienced by other travelers. The model assumes that players are instrumentally rational and have perfect knowledge of the game. It is also assumed that there is

Table 4 Payoff matrix of a two-player congestion game. *Source*: Levinson (2005)

Player 1	Player 2		
	Early	On time	Late
Early	$0.5 * (E + D)$, $0.5 * (E + D)$	$E, 0$	E, L
On time	$0, E$	$0.5 * (L + D)$, $0.5 * (L + D)$	$0, L$
Late	L, E	$L, 0$	$L + 0.5 * (L + D)$, $L + 0.5 * (L + D)$

common knowledge of rationality as well as consistent alignment of beliefs. A payoff matrix in the two-player congestion game represents costs by incorporating a penalty for early arrival (E), late arrival (L), and journey delay (D). Hence, both players try to minimize the costs for each scenario. Each vehicle has three options: to depart early, to depart on time, or to depart late. If both players depart at the same time, both players have an equal chance of suffering from the incurred penalty costs, and there will be congestion. For example, if both vehicles depart early, there will be only one that arrives early while the other will suffer journey delay. Thus, each player has a 50% chance of being early or suffering journey delay [see Levinson (2005)]. The payoff matrix is described in Table 4. As can be seen, the equilibrium solution depends on the values of E, L, and D. Several plausible solutions are discussed in Levinson (2005).

The concept of the construction of the payoff matrix is simple, yet powerful, in describing driving behavior and congestion from the micro-behavioral perspective. Nonetheless, it still lacks a sense of space and mobility dimensions. This analysis, therefore, adopts the concept of the two-player congestion game within the framework of the evolutionary prisoner's dilemma. Space and mobility, which play an important role in the emergence of congestion, are introduced and incorporated in the analysis.

2.1.4 Importance of spatial context

Physical space plays an important role in the emergence of urban phenomena from individual choices. For example, proximity to other neighboring agents in Schelling's segregation model is one of the contributing factors to urban segregation phenomena (Schelling 1971) and to the emergence of power laws in a city system (Mansury and Gulyas 2007). In Computer Prisoner's Dilemma Tournaments, Axelrod (1984) shows that spatial structure, in addition to evolutionary strategies, is an important factor in creating cooperation. The seminal work of Nowak and May (1992) examines two simple kinds of player, those who always cooperate and those who always defect, in iterated prisoner's dilemmas with the presence of a two-dimensional spatial array. They found that spatial context indeed plays an important role in agents' interactions.

Cohen et al. (1999) emphasize how context preservation can promote cooperation among adaptive agents in iterated prisoner's dilemma games. The relatively stable "neighborhood" of the agents over time, known as context preservation, enormously contributes to the emergence and maintenance of mutual cooperation. Context preservation also tends to increase local influencing (i.e., frequently interacted players become similar over time) and homophily (i.e., tendency to interact among the same players). Context preservation may refer to an agent's neighborhood. The more likely that the agents will meet again, the more they cooperate. Thus, the environment in which agents interact is one of the key factors in the emergence of cooperation. Power (2009) presents a spatial agent-based model of an N-person prisoner's dilemma to examine the cooperation among a socio-geographic community. The results show that agent mobility and context preservation can lead to different effects on the evolution of cooperative behavior.

3 Model description

3.1 Overview

3.1.1 Purpose

The spatial ABM presented in this paper provides a micro-foundation analytical framework for behavioral interactions of adaptive agents (motorists) in geographical spaces where they locate, migrate, and interact. By integrating strategic behavior based on congestion game and evolutionary prisoner's dilemma (EPD) into the spatial context, this spatial ABM serves as a platform to analyze an emergence of traffic congestion as a result of on-the-road interactions of motorists, using the data of Bangkok. Unlike previous studies of EPD, this study employs a more realistic spatial geographic space—one where agents locate and interact—in a GIS environment. Agents are mobile and can move along the road network. The model also provides visual representation tools of EPD.

3.1.2 Entities and state variables

The model comprises two major types of objects (known as "contexts"): city context and agent context, with their spatial locations contained in a GIS projection. The city context represents physical geographies—or built environments—and consists of three sub-contexts: building, road, and junction contexts, the latter two of which form a road network. The building context contains building footprints, representing a spatial extent of the building configuration. The other component of the model, the agent context, contains autonomous and self-interested agents whose spatial locations are stored in a GIS projection. The model structure diagram is shown in Fig. 2.

The city context contextualizes the actual physical surroundings—within which agents move and interact—in GIS; it is comprised of road, junction, and building contexts (See Fig. 2). Roads and buildings, which are the two GIS inputs, are prepared in ArcGIS. The road shapefile is a simple representation of road centerline, and the building shapefile is a polygon shapefile of building parameters. The road geography is stored in the road context, while the building geography is contained in the building context. The last component of the city context is the junction context. It contains

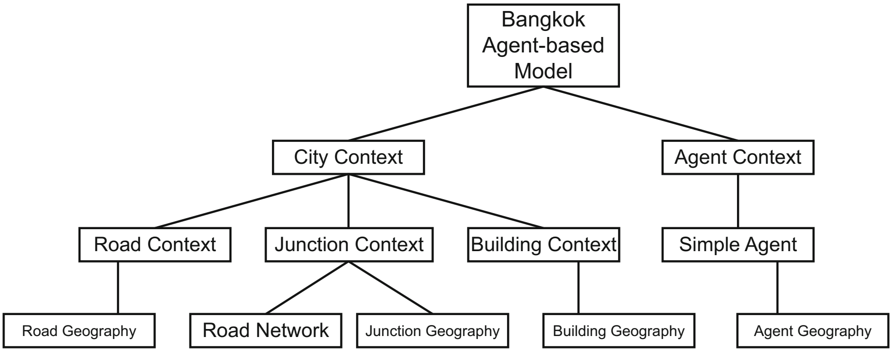

Fig. 2 Structure of a spatial agent-based model of Bangkok

road junction (nodes) and a road network. The junction context is constructed based on road geography from the input GIS road shapefile.

The agent context contains all agents, which are adaptive and autonomous, playing EPD to each other. Each agent is an object in the agent context, representing a motorist on the road who can decide to react and adapt. The geographical locations of all agents are also acquired from a GIS input, as in the city context, in the form of a point shapefile.

State variable includes the agents' strategy, cumulative payoff, total travel time to destination, and total number of trips. The study area in this study is the city center of Bangkok, Thailand. The GIS layers consist of roads, building footprints, and point locations of agents (or motorists in this case), which will be described in the following section. Although Bangkok is used in this study, the model platform is flexible and modifiable to incorporate different study areas—with different GIS inputs. One time step equals one second in real time.

3.1.3 Process overview and scheduling

The key element in this spatial agent-based model of a congestion game is the interaction of neighboring motorists on the road. In each simulation step, each motorist moves from an origin to a destination on an input road network. While traveling, each motorist can decide to drive responsibly or negligently in his interactions by playing EPD games with his neighboring motorists to accumulate his travel cost. It is assumed that all motorists have perfect information; therefore, the payoff value, representing the travel cost, of the EPD game is deterministic. After a destination is reached, a motorist will continue traveling to a new randomly selected destination until the simulation terminates. Travel demand is assumed to be unknown.

3.2 Design concepts

3.2.1 Individual decision-making

In a spatial agent-based model of a congestion game, an agent—representing a motorist on the road—makes a decision about their driving behavior. In the simplest form, play-

Table 5 Payoff matrix of a congestion game

Player1	Player 2	
	Cooperate	Defect
Cooperate	F_1, F_1	F_2, F_3
Defect	F_3, F_2	F_4, F_4

ers may choose to cooperate (e.g., driving responsibly and following traffic regulations) or to defect (such as violating traffic regulations or driving negligently).

The construction of a payoff matrix adopts the concept of the congestion game of Levinson (2005). Each player's decision takes into account the penalty—measured in terms of the value of time loss—of journey delay (C_d), being involved in an accident (C_a), and being fined by traffic police (C_f). Table 5 shows the payoff matrix of the congestion game. When both players choose to cooperate, each encounter has an equal chance of incurring costs of journey delay. If a player chooses to cooperate while the other defects, this player has to bear the cost of journey delay as well as the cost of some probability of having an accident. The other player that defects not only bears the cost of potential accidents but also has the possibility of being fined by the traffic police because of its reckless driving behaviors, for example, a moving traffic violation. If both players defect, each will bear all costs of journey delay, accidents, and being fined. The elements in the payoff matrix are defined as follows:

$$F_1 = 0.5^* C_d, \tag{1}$$

$$F_2 = C_d + \left(P_a{}^* C_a\right), \tag{2}$$

$$F_3 = \left(P_a{}^* C_a\right) + \left(P_f{}^* C_f\right), \tag{3}$$

$$F_4 = \left(0.5^* C_d\right) + \left(P_a{}^* C_a\right) + \left(P_f{}^* C_f\right), \tag{4}$$

where

C_d denotes costs of journey delay = 0.0083 THB/s,
C_a denotes costs of accident = 770 THB/case,
C_f denotes traffic violation fines = 400 THB,
P_a denotes the probability that an accident can occur in each turn = 0.00000004, and
P_f denotes the probability of receiving a traffic violation fine in each turn = 0.00000012.

The numerical values in the payoff matrix are derived from stylized facts, statistics reports, and previous studies related to transportation in Bangkok. As agents make decisions in every encounter, these values are normalized in a monetary value per second of time. The cost of journey delay per second (C_d) is estimated to be 0.0083 Thai Baht (THB) or around US \$0.0003. It is derived from the study of Dissanayake and Morikawa (2010) that estimates the hourly value of time of Bangkok commuters to be 30 THB, which results in a value of 0.0083 THB per second. The cost of an accident is calculated from a recent statistical report from the Royal Thai Police Central Information Technology Center. In 2011, there were 4669 traffic accident cases reported to the

Table 6 Numerical payoff matrix of a congestion game

Player1	Player 2	
	Cooperate	Defect
Cooperate	−0.00415, −0.00415	−0.00830, −0.00008
Defect	−0.00008,−0.00830	−0.00423, −0.00423

police, and it was estimated that the damage from these accidents was 3,598,000 THB, or around 770 THB (US $25) per case ($C_a$). An average fine for a traffic violation in Bangkok is 400 THB, thus being the value of C_f. The probability of an accident occurring (P_a) is calculated from the ratio of the number of cars involved in accidents to the total number of cars registered in Bangkok in 2011. Finally, the probability of receiving a traffic violation fine (P_f) is derived from the ratio of the number of cases where fines have been issued (Dailynews 2012) to the total number of vehicles registered in Bangkok. The values in the payoff matrix from these stylized facts are given in Table 6. Since the payoff represents costs, the values are shown in negative numbers. As can be seen, the matrix is one example of the prisoner's dilemma; each agent individually has an incentive to defect, but it is more socially optimal if both cooperate.

3.2.2 Individual movement

Figure 3 illustrates the overall flow of agents' movements in a simulation. At the beginning of each trip, each agent chooses a random destination, which is one of the buildings in the building context. Once a destination is selected, the route is formed, and the agent travels along the road to its destination. In a simulation, the agents' movements are restricted to the roads only.

As described by Malleson (2011), the algorithm of an agent's movement along the road involves a few steps. Suppose an agent starts at his home, and a random destination is selected. The first step is to identify the nearest junctions of an agent's origin position and destination. When these junctions are identified, a route is determined. To form a route between the origin and destination locations, a list of edges in the road network projection is generated using Dijkstra's shortest path algorithm. Once the route has been formed, a list of coordinates through which the agent must pass when traveling from the origin to the destination is also created. To generate a list of coordinates, all the edges that make up the route are iterated to find their corresponding road objects in the road geography, and eventually all the coordinates which form the geometry of these road objects are added to the list. As such, the agent's movement from its origin to its destination is restricted only to roads. After the list of coordinates along the route is generated, in each turn the agent can only move a certain distance from its current position. If the agent is currently not on a road segment, for example, the agent may be inside a building, so the agent is first moved to the nearest junctions (or nodes). The maximum distance of agent movement in each tick is exogenously defined. Virtually, this defines the "speed" of an agent's movement. Currently, the maximum

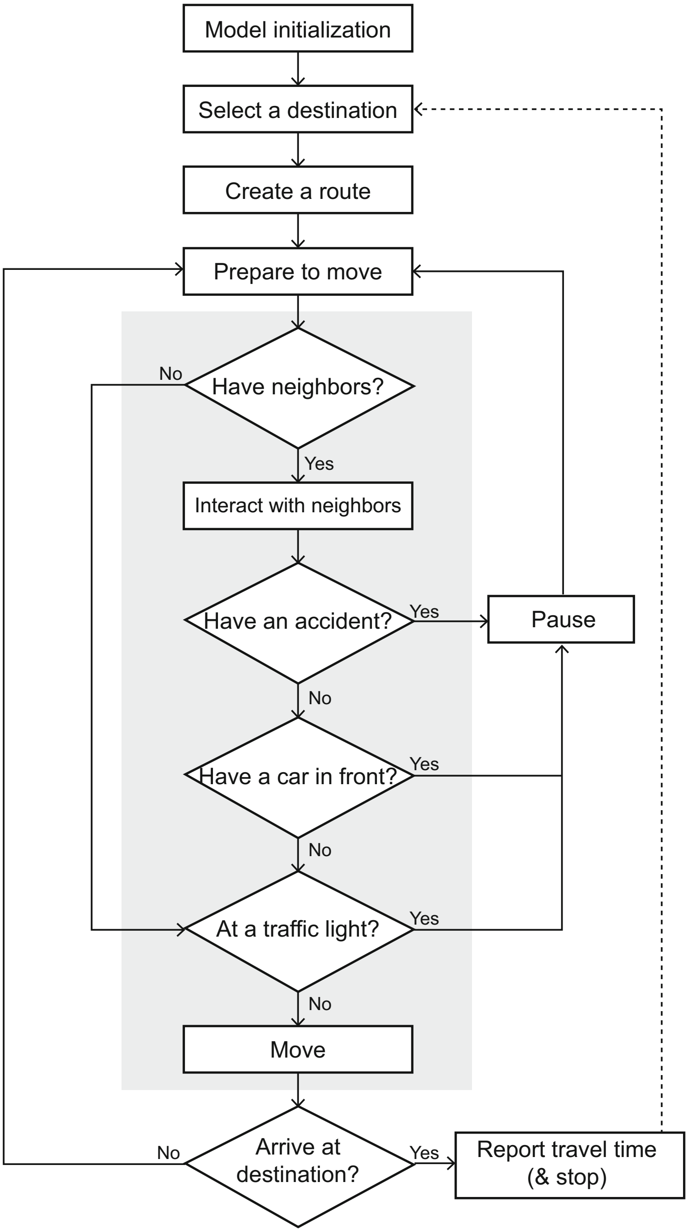

Fig. 3 Flow diagram of agent-based model of Bangkok

movement distance allowed in each tick is set at 5 m, or around 16 feet. Thus, if one tick is equivalent to one second in real time, an agent's speed is 18 km per h, which is an approximate average speed in Bangkok city center (Royal Thai Police Central Information Technology Center 2011). If an agent cannot move from one coordinate to the next in one turn (in other words, the distance between the two coordinates is greater than the maximum allowable travel distance), it will move toward the next coordinate by the defined maximum distance in one turn and continue the remaining distance toward the next coordinate in the following turn.

In addition, before beginning to move in each turn, each agent performs several checks, including determining the number of neighboring players and their locations. As shown in Fig. 3, decisions and actions shown on a gray background are decisions needing to be determined prior to moving in each turn. If an agent has at least one neighbor, it will interact with its neighbors, which is described in the following section. If not, the agent performs further checks, which are special movement features added in the model. For example, to avoid a collision, an agent may temporarily halt their traveling if they have a vehicle in front of them. At an intersection, an agent also temporarily stops moving when a traffic light is red and continues traveling when a traffic light turns green. For simplicity in programming, the traffic light control at an intersection allows vehicles to move from only one direction at a time. For instance, at an intersection, only vehicles from the east may travel while vehicles from the north, west, and south have to stop. The model also allows for the possibility of having an accident, depending on the strategy of an agent. Agents choosing the ALLD strategy have a higher probability of having an accident than agents choosing other strategies. If an agent is involved in an accident, it temporarily stops moving.

3.2.3 Individual sensing

Previous works have shown that context preservation is an important factor for the emergence of cooperation. Thus the agents' neighborhood is a crucial component for such cooperation since local influence—or "the mix of encounter"—can largely affect and sustain the cooperation (Cohen et al. 1999). The neighborhood of an agent, in fact, can be defined in many different ways, depending on the environmental context

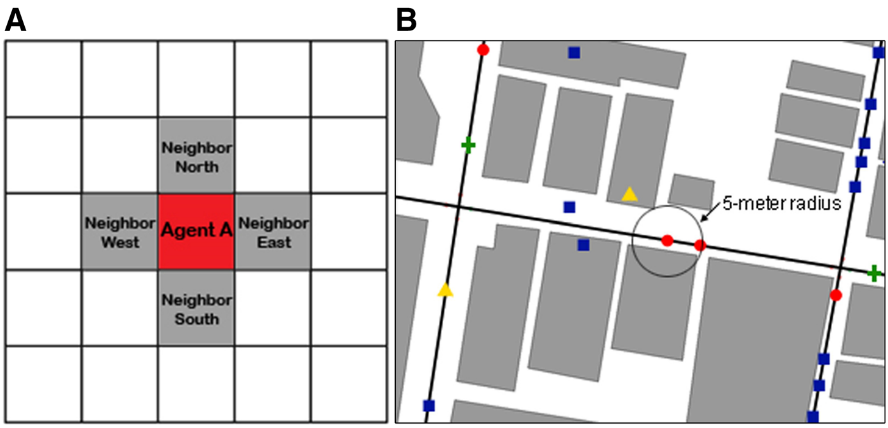

Fig. 4 Comparison of an agent's neighborhood in a grid context (*left*) and in a geographic information systems (*right*)

employed in the model. If an agent is located in a two-dimensional grid system (see Fig. 4a), its surrounding neighbors can be comprised of four cells (von Neumann) or eight cells (Moore).

Alternatively, an agent's interacting neighbors can be defined based on their proximity to other agents. If the distance between two agents is less than some threshold distance set by the analyst, these two agents are considered to be neighbors. The most commonly defined distance is straight-line or Euclidian distance. Using GIS layers for geographic locations of agents, an interaction neighborhood can be defined as agents situated within a specified radius buffer from Agent A (see Fig. 4b). Agents that are located outside of the buffered area are not considered the neighbor of Agent A and thus will not interact with Agent A. The major difference between grid space and GIS space is the variation in the number of agent's neighbors. While an agent in the grid may have a constant number of neighbors, four neighbors in this example, the neighbors of an agent in GIS space may vary, depending on an agent's and its neighboring agents' current positions.

In this spatial agent-based model of a congestion game, agents are said to be neighbors if they are located within a certain Euclidian distance from each other. That distance is currently set to be 5 m, which is approximately the length of a car. The number of neighbors of an agent may vary because of the movement of the agent. In every turn, as an agent moves along the road, its neighbor would change, depending on the agent's current position. It is also possible that at some turns, an agent may not have a neighbor at all. An agent itself is always included as its neighbor. Therefore, in every turn, an agent will always have at least one neighbor, that is, the agent itself. This variation in the number of neighbors certainly affects the interaction patterns of the agent, allowing for the analysis of the effect of spatial context on evolutionary behaviors of agents.

3.2.4 Interaction

After its neighbors are determined, an agent interacts with its neighbors to accumulate payoff—representing travel costs. In each turn, an agent will play N number of EPD games with its neighbor, where N denotes the number of neighbors. Since every agent is assumed to be rational and know perfectly the value in the payoff matrix, the payoff is deterministic. How the agent interacts with its neighbors depends primarily on its strategy. Following Cohen et al. (1999), this study employs a decision rule for the agent using a "binary" strategy as discussed in Sect. 2.1.2. As such, the strategy is deterministic. There are four strategies: ALLC, TFT, ATFT, and ALLD.

Once having interacted with its neighbors, the agent adapts to the best strategy from the previous encounter. To adapt to the best strategy, an agent first compares its score to its neighboring agents' scores. If the best score of the neighboring agents is higher than or equal to the agent's score, the agent then imitates the strategy of the neighboring agent with the best score. If the agent's score is the best among neighboring agents, the agent then imitates its own strategy. In this sense, suppose T denotes a time period (or the number of turns) in the simulation. The agent's strategy is driven by the agent's memories and lessons learnt from the previous encounters in period $T - 1$.

3.3 Details

3.3.1 Implementation details

The framework of this spatial agent-based model of a congestion game is based on the RepastCity2 model developed by Malleson (2011). The model is built using the Repast Simphony modeling system 2.0 beta software developed by Argonne National Laboratory (Repast Organization for Architecture and Design 2008, 2010).

3.3.2 Initialization

In period 0, the population is split with equal probability into four types of strategies: ALLC, TFT, ATFT, and ALLD. The initial location of each individual agent is at the center of a building in the city context. In every period afterward, each individual agent randomly chooses a building and route of travel to that destination. While traveling, an agent encounters other individuals, which are considered to be the agent's neighbors if located within a certain distance. Once the agent's neighbors are determined, the agent plays multiple EPD games with its neighbors and accumulates the payoff values. Since the agent is mobile, it is possible that the agent may have no neighbors at a certain point in time. If the agent has no neighbors, the agent will not play any games in that turn.

During the model initialization process, spatial extent is constructed from the input GIS shapefiles, and topological relationships of junctions and roads are built into a road network. Through iterating all road objects, junctions are created where two roads meet, and these junctions are added to the junction context and the road network projection. Meanwhile, the edge (or arc) connecting two nodes is created and added to the road network. The relationship of road objects in the road geography and road edges in the road network projections is preserved, linking the GIS projection to the network projection. By default, the map coordinate system of input GIS layers must be the geographic coordinate system. Thus, the coordinate system of all input GIS shapefiles in the model is World Geodetic System (WGS) 1984.

The area of the city context encompasses around 4 square miles, or around 10 square kilometers, in Pathumwan district. As illustrated in Fig. 5, roads are shown in black and buildings are in gray. The study area covers one of the busiest areas in Bangkok, with several intersections and commercial/office buildings. For simplicity, all roads in the city context represent two-way roads with one lane in each direction.

3.3.3 Input data

GIS input data—both building and road shapefiles—that form the spatial extent of the model are created by the authors by tracing them from a current Google Map. To construct a payoff matrix of the congestion game, the cost of an accident is calculated from a recent statistical report from the Royal Thai Police Central Information Technology Center.

Fig. 5 Spatial extent of city context

4 Results

4.1 Experiment settings

To examine congestion as a consequence of motorists' interactions, the analysis consists of simulations with three different initial conditions: (1) when all motorists always cooperate (ALLC), (2) when all always defect (ALLD), and (3) when all four strategies are mixed. The case when all agents always cooperate serves as a baseline when all motorists behave nicely, while the condition when all always defect serves as an

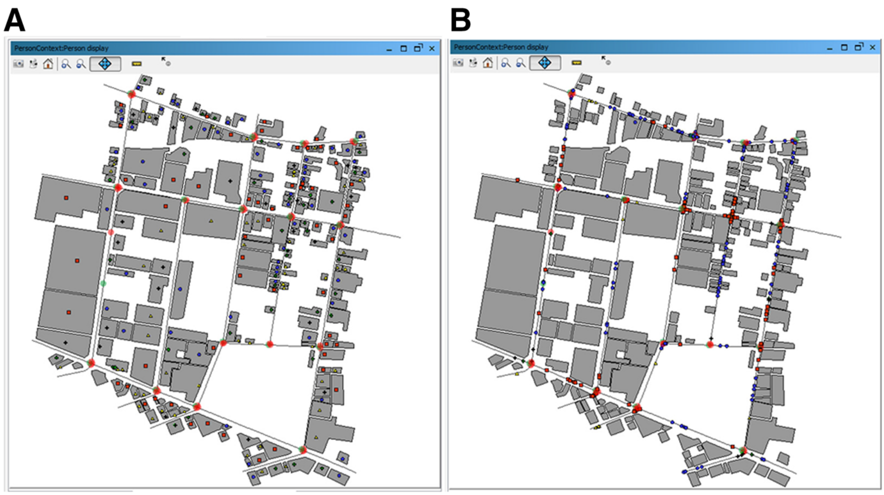

Fig. 6 Simulation interface at tick 0 (*left*) and 50 (*right*)

extreme case when everyone behaves badly. The hypothesis tested here is that when an increasing number of motorists behave recklessly (i.e., choose to defect) to save travel time, it inadvertently creates more congestion. The model simulation allows for testing such hypotheses. Congestion is evaluated using average travel time in every 50-tick interval. For each initial condition, a simulation is run for 5000 ticks. The travel time in milliseconds is reported and recorded when agents reach their destinations and complete a trip.

In the simulation graphic interface, each type of agent is symbolized differently in terms of both colors and shapes. Agents with ALLC, TFT, ATFT, and ALLD are shown in a blue circle, green cross, red square, and yellow triangle, respectively. If an agent changes its strategy, its graphic representation also changes. Traffic lights at intersections are shown in red and green circles for red and green lights. Figure 6 illustrates the simulation interface at times 0 and 50 for the mixed-strategy initial condition. As can be seen, all agents start at the internal point inside buildings and gradually move toward the nearest road and continue moving on the road afterward.

4.2 Observation on micro-foundation

Figure 7 illustrates the average travel time for each initial condition. As can be seen, although the results are based on one simulation for each condition, a condition with all ALLD agents overall has the highest average travel time. On average, the travel time in the scenario with ALLD agents is 102,629.72 ms, while the travel times of ALLC and mixed strategies are 79,921.02 and 85,469.56 ms, respectively. It suggests that when pursuing his own interest, an agent who always defects makes the society as a whole worse off. By driving negligently to avoid traffic, agents paradoxically create more congestion, and this congestion emerges as a result of the spatial interactions of all motorists.

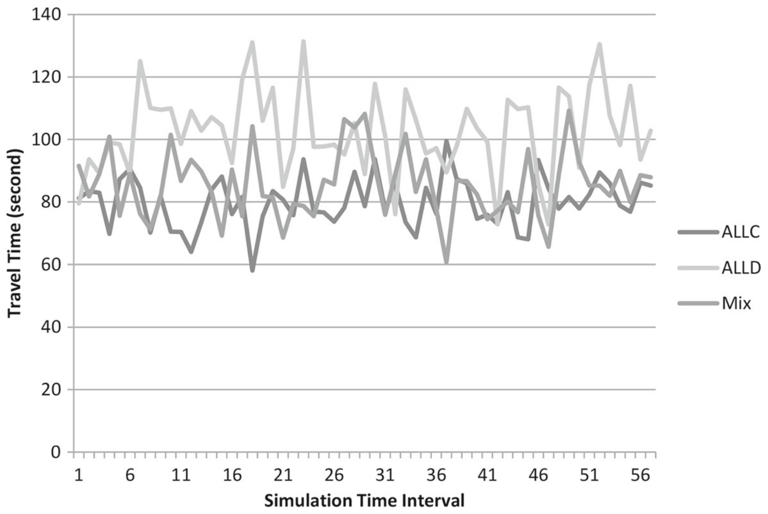

Fig. 7 Average travel time with three different initial conditions

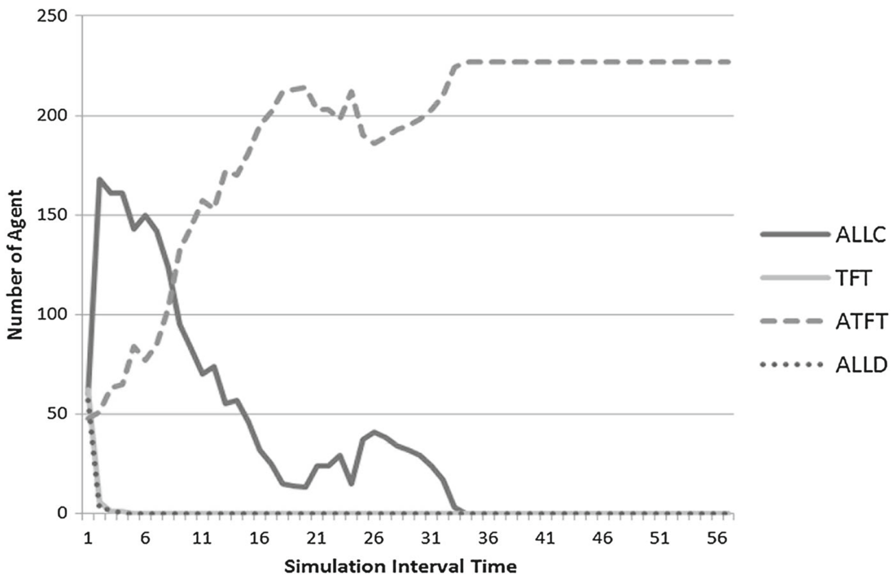

Fig. 8 Agents' strategies in mixed-strategy initial condition

Additionally, the effect of context preservation can be analyzed in the third initial condition (when all four strategies are mixed). As shown in Fig. 8, the agent's strategies are first dominated by ALLC but later converge to ATFT. The result suggests that ATFT seems to be the best strategy when an agent's spatial context is not preserved. As time progresses, when an agent moves, his neighbors change. As a result, an agent's context is not preserved, and an agent is less likely to cooperate. This profoundly explains motorists' behavior on the road. As motorists are less likely to sustain the

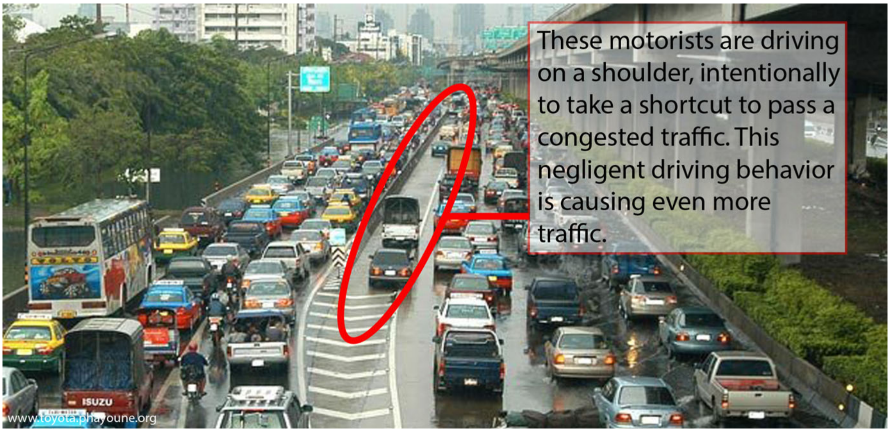

Fig. 9 Negligent driving behavior in Bangkok

same interacting neighbors for a long period of time, they are more likely to behave negligently and do not cooperate. The result supports the earlier findings of Cohen et al. (1999) and Power (2009) that agent mobility and context preservation can lead to different effects on the evolution of cooperative behavior.

This emerged congestion is common in Bangkok traffic. Figure 9 illustrates some examples of these negligent driving behaviors such as illegal overtaking by driving on a highway shoulder intentionally to pass through a traffic jam on other lanes. As these drivers may not necessarily "interact" with the same vehicles they just pass through, they choose to be negligent and not follow the traffic regulation. These negligent driving behaviors consequently cause even more traffic as these vehicles on this "additional" lane must eventually be merged to a regular lane. Dangerous lane changing, illegal overtaking, violating traffic signs, driving in the wrong way, speeding, and tailgating are also examples of negligent driving behaviors observed in Bangkok motorists. As this analysis shows, if there are many negligent motorists who are motivated by their own time-saving interest, they may cause even more congestion than if all motorists drive responsibly, as we have observed in traffic congestion in Bangkok.

5 Conclusion

Prisoner's dilemma is one extension of game theory that has long been used to analyze phenomena when individuals acting in their self-interest become worse off than if they had cooperated. Evolutionary prisoner's dilemma (EPD), in particular, incorporates adaptive agents in iterated games. In the EPD, context preservation is found to play a key role in the emergence of cooperation since cooperation tends to emerge if players are likely to encounter each other again in the future. Therefore, for each player, the interaction dynamic at the local scale is more important than what happens at the global scale. In this sense, the neighborhood of the agents is a key factor in the emergence of cooperation.

This paper develops visual representation tools to analyze strategic behaviors from a game theoretic perspective when spatial interactions and movement are possible. It extends the conceptual framework of EPD to examine road users' behaviors in a setting of roads in Bangkok city center. The analysis assumes that while traveling, an agent's decisions take into account the costs associated with journey delays, accidents, and traffic violation fines. This paper argues that motorists violate traffic regulations—intentionally acting negligently—because of the belief that doing so saves travel time. Paradoxically, if enough motorists share this belief, the result is even more congestion. Overall traffic is much slower when all motorists behave irresponsibly—or always defect, in comparison with scenarios when more drivers behave responsibly. Congestion, thus, emerges as a result of strategic time-saving behavior.

In addition, when an agent's context is not preserved—that is, when an agent's interacting neighbors are not constant—an agent is less likely to cooperate (or behave nicely). As a result, an emergence of cooperation cannot be observed in the simulation. This result supports the earlier findings of Cohen et al. (1999) and Power (2009) that agent mobility and context preservation play an important role in the evolution of cooperative behavior.

This modeling framework of travel behavior can be extended in several possible ways. Further extensions include incorporating other road networks in the model and allowing for agent's heterogeneity such as types of vehicle or characteristics of drivers. The model can also potentially incorporate a number of policy analyses such as studying an increase in traffic violation fines, the effectiveness of traffic law enforcement, and congestion pricing.

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