Peer-to-Peer Shared Ride Systems

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Abstract. Shared ride systems match the travel demand of transport clients with the supply by vehicles, or hosts, such that the clients find rides to their destinations. A peer-to-peer shared ride system allows clients to find rides in an ad-hoc manner, by negotiating directly with nearby hosts via radio-based communication. Such a peer-to-peer shared ride system has to deal with various types of hosts, such as private cars and mass transit vehicles. Their different behaviors affect the negotiation process, and consequently the travel choices. In this paper, we present and discuss a model of a peer-to-peer shared ride system with different types of agents. The behavior of the model is investigated in a simulation of different communication and way-finding strategies. We demonstrate that different types of agents enrich the choices of the clients, and lead to local solutions that are nearly optimal.

1 Introduction

Research on geosensor networks is typically concerned with the efficient extraction of information of sensor observations, hence, looking into hardware, protocols, routing of messages, and data aggregation. The research presented in this chapter is different in some respects. First of all, its focus lies on movement of the nodes, not on movement of information. The investigated geosensor network consists of nodes that have individual, specific travel intentions. If two nodes meet, one of them can ride piggy-back on the other one for reasons like saving fuel or traveling faster, depending on the abilities of the two nodes. Secondly, this geosensor network allows for different classes of nodes. In applications, one will distinguish transportation clients from transportation hosts. Furthermore, different clients and hosts can be distinguished. For example, there may be clients that can move only with a host, otherwise they are static, or there may be clients that travel significantly slower than hosts. Finally, this geosensor network underlies the well-known communication constraints of all geosensor networks. Nodes have to communicate to match clients with hosts, but communication is limited to local neighborhoods because of scarce resources in terms of battery and bandwidth, and because of a fragile communication network topology due to node mobility.

The interesting research questions in this context are about communication and trip planning strategies of nodes, about global optimization of trips from local transportation network knowledge, and about the general behavior of large transportation geosensor networks with autonomous nodes. This chapter will address and illuminate the questions by a concrete realization: a shared ride system for persons traveling by multiple modes in the city.

Movement of people in a city forms a complex system. It includes the street network and other ways of traveling, traffic rules, traffic infrastructure (e.g., traffic lights, signs) as well as cognition, decisions and actions of intelligent, autonomous agents such as pedestrians and vehicle drivers. This complex system is burdened by more and more traffic in expanding cities. In this situation a peer-to-peer shared ride system can provide relief to the critical situation: it enables people to negotiate in an ad-hoc manner for ride sharing, and thus, helps reducing traffic, increases urban accessibility, and improves the integration of different modes of transport. In such a system, pedestrians are the agents with transport demand, called clients, and vehicles, or hosts, provide the transport supply. Finding rides in an ad-hoc manner is accomplished by local negotiation between these agents via radio-based communication.

A peer-to-peer shared ride system has to deal with various types of agents, such as private cars and mass transit vehicles, or mobile and immobile clients, to cope adequately with the complexity of urban movements. The agents' different interests, capacities and behaviors affect the negotiation process, and consequently, the trips undertaken. For example, hosts can be distinguished by their travel speed, their passenger capacity and their fare structure, and clients can be distinguished by their mobility.

In this situation a client cannot stay with a simple preference for one mode of traveling, that is, one type of hosts. For example, in general a rushed client would prefer hosts can deliver a quick and direct trip: taxis. On the other hand, taxis can be in high demand during peak travel times and catching trams, trains or buses can be an alternative: they may travel slower but might reach the destination earlier depending on traffic. Hence, in this paper we present and discuss a model of a peer-to-peer shared ride system with different types of agents.

Agents, that is, clients and hosts in peer-to-peer shared-ride systems have knowledge of their environment. They can collect and transmit information from/to their neighbors. Frequently agents have choices. They have preferences, various optimization criteria, such as money or time, and are able to make current optimal decisions based on their knowledge. However, for practical reasons agents have only local and current knowledge of their environment. Previous research [1] investigates the ability to make trip plans from different levels of local knowledge. It shows that a mid-range communication depth is both efficient (needing less communication messages than complete current knowledge) and effective (leading to a travel time comparable to complete current knowledge). This investigation was based on a simulation with homogeneous hosts and an immobile client. This paper poses the hypothesis that involving other types of agents, the trips will change significantly, but mid-range communication is still both efficient and effective compared to other communication strategies.

This hypothesis will be approached by simulation. The simulation is realized as a multi-agent system, allowing us to model and understand individual behavior of different agents. The approach requires identifying and specifying the essential aspects of an urban shared ride system, implementing them in a multi-agent system, and then running large numbers of random experiments to generate the required evidence. The model can be investigated by systematically varying the design parameters and studying the peer-to-peer shared ride system behavior.

This paper has the following structure. Section 2 reviews previous and related research. Section 3 discusses the types of agents in shared ride systems. Section 5 presents the design of a multi-agent simulation, and the simulation results are provided in Section 6. Section 7 concludes with a discussion and future work.

2 Literature review

This review consists of a literature overview of shared ride systems in general, and of agent-based simulation of shared ride system in particular, with special attention to previous research on a peer-to-peer shared ride system.

2.1 Shared ride systems

In the real world, shared ride systems exist in many forms and names, such as *carpooling*, *vanpooling*, *dial-a-ride*, or *find-a-ride*. Shared ride systems also have various levels of technological support, such as being based simply on social convention, or using a centralized database with pre-registration and/or pre-booking via a Web interface.

Carpooling/Vanpooling can be seen as a prearranged shared ride service between home and workplace to save up parking spaces [2]. Traditional carpooling/vanpooling services are organized by private companies and are not door-to-door. People with regular commuting schedules usually meet in a place to share vehicles running on prearranged times and routes. Van pooling is limited by the provider's service area and not viable for areas or individual origins or destinations that do not have the critical mass of people using the service. New users can only participate in existing poolings, or they can create a new pooling with others.

Mass transit systems, like the underground, trains, buses and trams, run on predefined schedules and routes. Being government funded or subsidized, the fares are typically lower than the costs of private means of transportation. In addition to guaranteeing mobility and access for everybody, this shall also encourage people to mitigate individual car traffic. However, such a shared ride is restricted to fixed time schedules and routes, which is less comfortable than many private transportation alternatives.

To better satisfy users, dial-a-ride systems have been initiated. Dial-a-ride systems can offer more flexible and comfortable door-to-door rides, chiefly by commercial vehicles and taxis [3]. To utilize the vehicles' passenger capacity, drivers can pick up other passengers before reaching the destination of the first customer. The authors implement a dynamic dial-a-ride system, which can re-optimize routes after picking up new customers during services. Therefore, this dynamic dial-a-ride system supports a many-to-many service—customers have different departures and destinations—and does not need booking in advance.

Web-based shared ride systems include Google Ridefinder¹, Ride Now!², Ride-Pro3³, eRideShare⁴, or Mitfahrzentrale⁵. These applications provide textual Web in-

http://labs.google.com/ridefinder.

² http://www.ridenow.org

³ http://www.ridepro.net

⁴ http://www.erideshare.com

⁵ http://www.mitfahrzentrale.de

terfaces to attract registrations of shared ride clients and hosts, and are maintained by local and regional agencies with central databases. Mediated trips are usually regional or national travels, with inner urban travels generally not catered for. To request or offer a ride, users (clients and hosts) need to provide their home addresses, cell phone number, email addresses and requested trip details. Then the databases match requests and offers immediately, and feed back a contact list of potential shared ride hosts or clients. The choice is left to the users who can email or call their selections. Agencies need high-powered workstations, database servers and internet connectivity to run such an application. Personal computers or mobile devices with Internet connectivity are necessary as data terminals for the users.

2.2 Agent-based simulation and shared ride applications

Simulation is an accepted approach to investigate the behavior of complex systems in general, and of traffic [4, 5] and sensor networks in particular. Simulation allows to study information spreading in mobile ad-hoc sensor networks, MANETs [6, 7], as well as in more specialized vehicle ad-hoc sensor networks, VANETs [8]. For the present problem, a geosensor network of heterogenous nodes with travel intentions, with autonomous travel behavior, and spatial restrictions to move, a multi-agent system is chosen for its simulation. Agent classes are designed to represent the different types of moving agents.

Several established agent-based simulation libraries exist that simplify modeling. Object-Based Environment for Urban Simulation, *OBEUS*⁶, has been developed as a simplest implementation of geographic automata systems in .Net [9, 10]. It is designed for urban processes and built in a cellular automata model with transition rules in form of functions. Entities in *OBEUS* can be one of two types, either mobile or immobile entities. In *OBEUS* no direct relationship is allowed between non-fixed objects. That means that *OBEUS* is not suitable for our simulation of locally communicating mobile agents. *Swarm*⁷ is one of the popular libraries based on Objective C and has a Java wrapper. *RePast*⁸ is a newer Swarm-like conceptual toolkit [11]. *RePast* is a free open source toolkit core in Java, while it has three implementations in Java, .Net and Python. Both approaches support to program multi-agent systems that are composed of larger numbers of agents with functions describing their behavior. *RePast* was used successfully for a large-scale peer-to-peer shared ride system simulation [12]. However, installing and using libraries is in itself a larger effort due to the constraints imposed by a given system design, so we decided to develop our system from scratch.

Previous research on a peer-to-peer shared ride system proposes a trip planning model on ad-hoc mobile geosensor networks [13]. The peer-to-peer system was designed to solve the problem of capacity limitations of centralized travel planning systems with large numbers of concurrent users in large dynamic networks and ad-hoc ride requests. The authors demonstrate that without a central service, shared ride trip planning with limited knowledge is possible and computationally efficient in a dynamic environment. They later implement this scenario with a simulation, in which clients with

⁶ OBEUS can be downloaded from http://www.geosimulationbook.com

⁷ http://www.swarm.org

⁸ http://repast.sourceforge.net

transportation demand, and hosts with transportation supply communicate on a radio base to negotiate and plan trips in a continuously changing environment [14, 1]. They design a mechanism for the negotiation process and investigates three communication strategies with different communication neighborhoods. Hosts are homogeneous, and clients are immobile in these experiments. The authors conclude that mid-range communication strategy in mobile geosensor network is both effective (leading to travel time comparable to complete current knowledge) and efficient (leading to less communication messages than those for complete transportation knowledge) compared to unconstrained or short-range communication.

3 Agents in peer-to-peer shared ride systems

Participants in peer-to-peer shared ride systems, to be modeled as geosensor network nodes later, are capable of perceiving their environment, of collecting information and making decisions, and of communicating where necessary. Particularly, peers are mobile, and some can move with other peers. In this section, immobile and mobile clients are identified, and three typical kinds of hosts (i.e., mass transit, taxis and private cars) with distinct economic and operational characteristics, in order to reflect better the properties of realistic shared ride systems in a simulation.

3.1 Clients

Real world clients have a desire to travel to their destinations and depend on rides from hosts. Immobile and mobile clients can be distinguished. Immobile clients rely completely on rides in order to move. Mobile clients can alternatively move on their own, but far slower than taking rides. The mobility of clients can depend on their preferences, their luggage, or their company (e.g., children).

Some clients might stick to preselected routes (e.g., the shortest) and only look for rides along their route. Alternatively, clients with a desire to optimize routes using cost functions such as travel time, number of transfers, or trip fares, will accept detours, as long as they promise to reach the destination for lower cost. For some clients, shorter travel times are more important than trip fares, while budget clients favor cheaper rides. Fewer transfers are more attractive to clients who appreciate comfortable trips, while scenic views would be a cost function (to maximize) for tourist clients. Frequently clients balance these factors with some subjective weighting. Furthermore, clients can have other preferences, such as for types of hosts, or for specific profiles of vehicle drivers.

Another factor to consider is the knowledge of the client. While the general assumption is that the client knows the street network for trip planning, it makes a difference whether the client knows also the mass transit network and time tables, or typical traffic patterns in the city (e.g., main streets experience more traffic than others).

3.2 Hosts in mass transit

Mass transit in a city includes buses, trams, trains, underground, and ferries. Generally, mass transit vehicles carry more passengers compared to other means of transport, al-

though with less comfort and privacy. Travel fares are relatively cheap, especially with flat fare structures on longer distances, or with tickets that are interchangeably valid on various modes of mass transit. Often fares are charged by time only, regardless how long the trip.

Mass transit follows fixed timetables, typically with larger gaps between midnight and early morning and varying frequency over the day. They run on predefined routes back and forth, and passengers are only allowed to get on or off at stops. This means that mass transit does not provide door-to-door transport, and some areas are not served at all. Some means of mass transit run on their own line network, e.g., trains, trams and subway, or have reserved lanes, and are less affected by other traffic. This means that mass transit vehicles may be faster than street traffic bound vehicles.

3.3 Taxis

Taxis are more comfortable and convenient compared to mass transit. Taxis can reach every location in a city's street network, and can be called at any time of the day. Passengers can head directly to their destinations without compulsive intermediate stops or transfers. Detouring, change of destination, and stopovers are also possible during travel.

The main disadvantages of taxis are a limited passenger capacity, and correspondingly, a high trip fare. Normally, taxis have about four seats for passengers, but these are only shared by a group sharing the same trip. Taxis are charged by a combination of travel distance and time; sometimes a flag fall is added. This means that taxis are more suitable when time or convenience is more valued than money.

3.4 Private cars

As hosts of shared rides, private cars are similar to taxis in some respects: they share the advantage of comfort, and the disadvantage of low passenger capacity. The difference is that private cars are owned by their drivers, and hence, are considered as private space, or proxemics [15].

Nevertheless, private car drivers may be willing to offer a ride if they get some incentives. But they are unlikely to serve clients off their route. Rather they pick up clients anywhere along their own trip, and give them a ride along their own route. Private car drivers may also have rigid interests and preferences in selecting clients, such as non-smoking clients, or clients of a specific gender.

Incentives for the car drivers could be nonmonetary, such as being allowed to use high-occupancy vehicle lanes with passengers on board. Even if they charge fees proportional to the traveled distance, their rates will be lower than taxi rates because the car drivers' interest is mostly sharing costs.

4 Communication in peer-to-peer shared ride systems

Peer-to-peer communication in a shared ride application enables nearby agents to collaboratively solve the shared ride trip planning. To make optimal decisions, agents need

to consider all transportation information. However, in dynamic traffic, agents have to make decisions with local knowledge only. This section discusses high-level communication protocols and strategies, the agents' negotiation mechanism and data collection in a peer-to-peer shared ride system, as they are proposed in the literature and studied in simulations [1].

4.1 Communication protocol and strategies

In a peer-to-peer shared ride system, the trip planning clients depend on transportation information from hosts. However, peer-to-peer communication for real-time decisions in dynamic street traffic enables only local communication strategies. This means an individual client may not reach or may not want to reach all hosts in the street network, and hence, has to plan a trip with local knowledge only. Nagel suggests that trip plans always include a start time, a start position, a destination and a sequence of nodes in between [5]. In shared ride planning, agents are additionally interested in the agents involved in the trip, arrival times, and travel fare. To enable negotiations between agents for trip plans, a communication protocol is designed for messages of the structure specified in Table 1. The details of the communication model and protocol are specified elsewhere [1].

Table 1. Message elements.

| | Field | Type | Description |
|---|--------|--------|--|
| 1 | | char | request r , offer o , booking b |
| 2 | | [node] | requested or offered route |
| 3 | time | int | start time of the route in the message |
| 4 | agents | [int] | record of all identifiers of agents that transfer this message |
| 5 | - I | float | speed of the original sender of this message |
| 6 | fare | float | travel fare of the offered route |

In a peer-to-peer system agents radio broadcast messages to their neighbors. Their radio range is limited according to the broadcasting technologies and the broadcasting power. Distant agents can be reached by forwarding messages (multi-hop broadcasting). For a peer-to-peer shared ride system the communication window—the synchronized time all agents listen and broadcast—requires to be long enough to accomplish a complete negotiation process, consisting of a request, offers, and a booking. So far trip planning with unconstrained, short-range and mid-range communication has been investigated in simulations. Unconstrained communication means that messages flood to the deepest agents in network, as long as agents are connected. Short-range communication means that agents only communicate to agents within their radio range (single-hop). In mid-range communication, agents forward messages for several hops. The negotiation process will be simulated for different communication ranges to investigate trip planning with different levels of transportation network knowledge. However, it is clear that the unconstrained communication strategy is not feasible in reality and used here only as a reference for the trip planning with (theoretically) maximum real-time information.

4.2 The negotiation mechanism

The mechanism to process the negotiations is shown in Figure 1. Clients initiate a negotiation by sending a request. Hosts respond with offers, clients make a selection, and the negotiation finishes with a booking made by the client. The three communication phases happen sequentially within one communication window. All requests, offers and booking messages are in the format of *message*, and are identified by *type* and the original sender in *agents*. After each negotiation, communication devices fall asleep to save energy, and agents move until the next negotiation process happens. Agents do not keep previous negotiations in memory. Therefore, there is no cancelation process integrated, instead booked rides are regarded as being canceled when no rebooking/confirmation happens in the following negotiation.

| t_i | | | | t_i | +1 | | | | t_{i+2} |
|-------|----------------------|-------------------------|------------------------|--------------|----------------------|-------------------------|------------------------|--------------|-----------|
| | Time interval | | | | Time interval | | | | |
| | Negotiation phase | | | Moving phase | Negotiation phase | | | Moving phase | |
| | Client sends request | Hosts respond by offers | Client plans and books | | Client sends request | Hosts respond by offers | Client plans and books | | |

Fig. 1. The cycle of negotiations and movements within two time intervals.

So far, only one client is generated in an individual simulation. All hosts serve this single client.

5 Formalization in a multi-agent simulation

This section presents a specification of a peer-to-peer shared ride simulation, with the types of agents (i.e., geosensor nodes) and their behavior as discussed above. The simulation is implemented in an object-oriented architecture using Java. Design details of the simulation model and related algorithms are elaborated by [16].

In our peer-to-peer shared ride system, agents have knowledge of their locations within the street network, negotiate with their neighbors for shared rides, make decisions according to their desires and intentions, and travel until the next negotiation takes place. Therefore, this system can be seen as a geographic automata system [10]: it has states, and state transitions, in particular the movements.

To implement geographic automata systems, Benenson and Torrens [10] suggest establishing a spatially restricted network with immobile and mobile agents, neighborhood relationships and behavior rules. Due to their interest on urban objects, such as buildings or residential addresses, they use a cellular network. In contrast, agents in

shared ride systems move in street networks, and hence, we use a grid network to model a real street network, with nodes representing street intersections and edges the street segments. Agents run in the grid network, and negotiate in an ad-hoc manner for ride sharing.

5.1 Agent parameters and behavior

Agents are designed in a class hierarchy (Figure 2), because they all have some common features and behavior. These common features and behavior are identified and encapsulated in the base class *agent*.

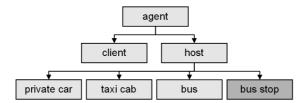


Fig. 2. Class hierarchy of agents.

Common features include the agent's identifier, its speed, its type, its state, its location in the current simulation environment, some information on its travel plans, such as the destination, and a temporary container for negotiation messages. The travel route contains departure and destination, and for some agents the nodes in between. For investigation purposes, a second container stores details of booked shared rides. Common behavior includes how to move to the next node, how to listen to neighbors and how to obtain knowledge about current position and state.

The classes *client* and *host* are derived from *agent*, and have additional properties and characteristic behavior. Their states, travel routes and current position can change over time, but type and speed are constant within a simulation.

5.2 Client agents

In the simulation, there are two types of clients: immobile clients, taking rides only, and mobile clients that are also able to move. The first type of client needs to be picked up from their location. The second type of client is able to move, which enables them to move to another location if they can get a ride there sooner. For clients, a (time-dependent) shortest path algorithm is needed for trip planning. The algorithm implemented is the heuristic lifelong planning A* algorithm [17]. This algorithm is adaptive to the dynamic traffic network. Given various cost functions (e.g., travel time or trip fare), this algorithm allows clients achieving different goals such as the quickest or the cheapest trip.

5.3 Host agents

There are three kinds of hosts in this simulation: private cars, taxis and mass transit. These hosts vary in their mobility, in their routing flexibility, in their passenger capacity, and in their economic models. Implemented hosts have two modes to respond to requested trips: they can offer to share sections of their own travel plans that match with requests, or they can leave their predefined travel route and make a detour for clients. A third alternative—hosts offering their travel route ahead no matter how relevant this is to a request—would only increase the communication costs.

5.4 Quality of trip planning

Local communication provides limited knowledge for clients, accessing only the travel plans of nearby hosts for shared ride trip planning. This knowledge is limited from a spatial ('nearby', which depends here on the communication strategy: short-range, midrange, or unconstrained) and temporal perspective ('now'). With this knowledge, clients in most cases can only choose sub-optimal trips. To investigate the consequences, an observer agent is designed in the simulation to enable a hindsight investigation of a global optimal trip. The observer is capable of monitoring the entire transportation network within the geosensor network. This global optimal trip can be compared with the client's trip to evaluate trip quality in the simulation.

6 Simulating shared rides with diverse agents

The specified peer-to-peer shared ride system simulation is tested for different types of agents. For the purpose of the test, travel time was chosen as the optimization criterion to look for the fastest trip. The simulation produces output in the form of text, which can be stored or visualized. Each result presented in this section summarizes 1000 simulation runs. For the experiments, hosts were parameterized according to Table 2.

| | Туре | Capa- city | Speed | Route | Detour | Fare rate | Others |
|---|--------------|---------------|-------|------------|--------|-----------|-------------------------------|
| 1 | private car | 2 | 1 | fix | FALSE | 0.5 | |
| 2 | taxi | 1 | 1 | variable | TRUE | 1 | flag fall is 1 |
| 3 | mass transit | 10 | 2. | predefined | FALSE | _ | schedule: one-off charge is 2 |

Table 2. Parameter settings of various host types.

6.1 Global optimal trips compared with sub-optimal trips

This experiment compares global optimal trips, computed posteriori for each simulation, with the client's trips made with two different communication strategies: midrange (comRange = 3) and unconstrained (comRange = 20) in a grid network of 10×10

nodes (the radio range is generally set to one segment). In this experiment the client is immobile and follows the geodesic route from node (3,5) to node (8,5), that is, the trip is in the center of the network and has a length of five segments. Homogeneous hosts of type *private car* are generated at random locations and with random routes of twelve segments length. Host density, defined as the proportion of the number of hosts and the number of nodes of the grid network, is fix. Figure 3 shows the average travel times of trips made versus the average global optimal travel time for various host densities.

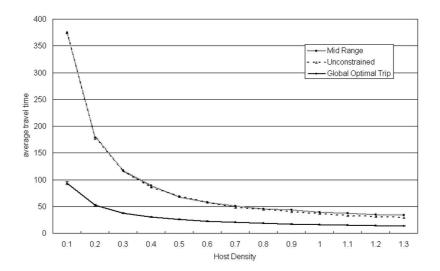


Fig. 3. Comparison of global optimal trips vs. sub-optimal trips realized by mid-range and unconstrained communication strategies.

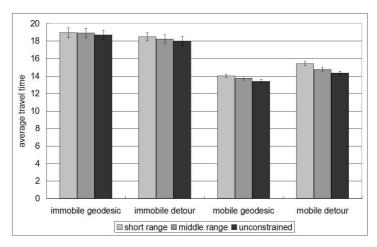
The experiment shows two significant results. First, a mid-range communication strategy is acceptable for all host densities; the unconstrained strategy, which is not feasible in practical applications, would improve travel times only marginally. Secondly, even complete current transport network knowledge as provided by the unconstrained strategy reaches only sub-optimal results, not considering future travel opportunities in time. – Since global knowledge is not accessible by clients, global optimal trips are not considered further in this paper.

6.2 Heterogeneous clients under diverse communication strategies

This experiment compares the efficiency and effectiveness of diverse communication strategies: short-range (comRange = 1), mid-range (comRange = 3) and unconstrained (comRange = 20) in a grid network of 10×10 nodes. There are four types of clients looking for the fastest trip: 1) an immobile client who sticks to the geodesic route, 2) an immobile client who is willing to make detours, 3) a mobile client who sticks to

the geodesic route, and 4) a mobile client who is willing to make detours. Each client departs at (3,5) and heads to the destination at (8,5). Mobile clients have a walking speed of $v_c = 0.25$ edges per time unit, while the homogenous host speed is $v_h = 1$ edge per time unit. The 72 hosts are all private cars.

Figure 4a shows the average time of shared rides by various clients, and Figure 4b shows the corresponding numbers of broadcasted messages. The experiment demonstrates again that (short-range and) mid-range communication delivers trips nearly as fast as unconstrained communication, for all densities of hosts. It also shows that short-range and mid-range communication produce much less messages than unconstrained communication. Furthermore, the client's ability to move and their flexibility to make detours make a significant difference in travel time. Mobile and flexible clients, due to their increased choices, have advantages over immobile or inflexible clients.



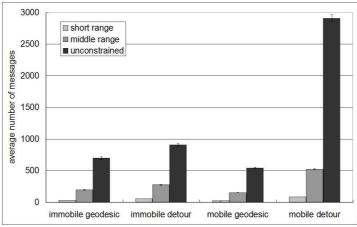


Fig. 4. Comparison of trip planning under three communication strategies.

6.3 Geo-routing quality with heterogeneous hosts using local knowledge

This section investigates a case with mobile, flexible clients in a transport network of various types of hosts in a grid world of 20×20 nodes. Mass transit is introduced as two bus lines (Figure 5), with one bus line partially overlapping with the direct route of the client. One new type of agent is the *bus stop* which is a static agent participating in negotiations and knowing the bus schedules.

Five experiments have been conducted, all with the same density of transportation hosts but with different proportions: 1) 144 private cars only; 2) 96 private cars and 48 buses (12 buses run in each direction of the two bus lines); 3) 96 private cars, 48 buses and 24 bus stops to help transferring bus travel information; 4) 96 private cars and 48 taxis; and 5) 48 private cars, 48 taxis, 48 buses and 24 bus stops. The average travel time and number of messages are shown in Figure 6.

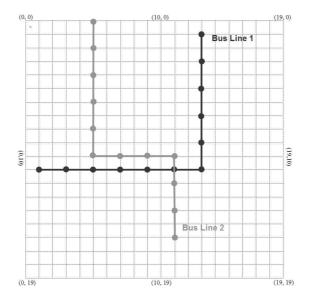
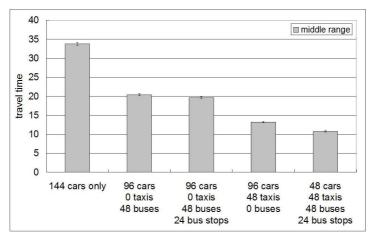


Fig. 5. The two bus lines in the grid street network.

The results show that the mix of host types has a significant influence on travel times as well as on communication efforts. In general, the presence of taxis in the network reduces average travel times, since once a taxi has picked up the client, the client travels along the shortest path. Buses also reduce the travel time because they are assumed to travel with double speed of cars (Table 2). Bus stops do not seem to have that importance, but this may be distorted by the relatively dense bus intervals in this experiment.



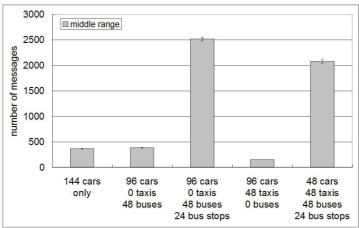


Fig. 6. Trip planning using local knowledge in multi-modal traffic.

6.4 Mobility models of agents

Up to now, private cars and unoccupied taxis are traveling by random. In a more sophisticated agent mobility model host agents may have a preference of traveling *central* streets [18, 19]. One of these models assigns connected segments of the grid street network to *named streets*. In this heterogeneous network of named streets, centrality was determined by *betweeness centrality* [20] and used to attract host traffic proportionally.

Clients aware of this behavior of hosts prefer to look for transfers at central street intersections, because there they have higher chances to find connecting hosts. To investigate this mobility model, experiments have to focus on the various behaviors of agents with different knowledge of the centrality in the street network. In the first experiment, the 120 hosts have no knowledge of centrality, and simply employ a random mobility model. Accordingly, the clients do not consider centrality either and follow strictly the graph geodesic between start and destination. In the second experiment, hosts have knowledge of centrality and adapt their mobility. Clients in this experiment still do ignore this knowledge and apply their traditional trip planning strategy. In the third experiment, finally, the clients consider centrality in their trip planning by favoring rides that end at central intersections.

Figure 7 visualizes the host distributions in the chosen named street network, where the hosts use the knowledge of central streets. The distribution of hosts is no longer equal, and the pattern shows the linear effects of long streets.

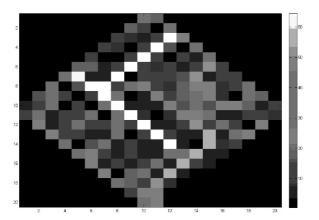


Fig. 7. Visualization of the host distributions, demonstrating a mobility model recognizing main streets and side streets in a grid street network.

Then Figure 8 presents the results of the three experiments: the bars showing average travel times, and the points connected by a line showing the average number of messages. The smaller improvement of travel times between the first and the second experiment can be explained by the different qualities of the shape of the host routes:

In average, the new mobility model leads to more elongated host routes than random movement, and hence, a single ride is in average more useful for the client. But more impressive is the advantage for the client when adapting to the travel patterns of hosts, as shown in the third experiment. At the same time the numbers of messages increase because the clients are traveling through streets with more traffic.

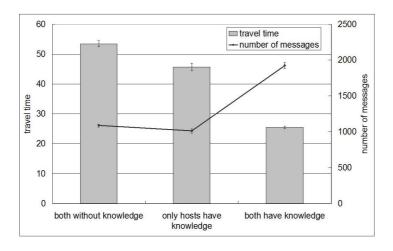


Fig. 8. Comparison of agents having different level of knowledge.

6.5 Multi-criteria optimization

The previous experiments were conducted on the assumption that clients want fastest trips. Nevertheless, in the real world people consider more factors when planning their trips. Other considered factors include the travel fare, the convenience (in terms of numbers of transfers), comfort, or security. More criteria make the planning of trips more complex: to make an optimal decision, people need to balance various criteria. This means the decision may not be optimal regarding a single criterion but good enough as a whole. In this section experiments are designed to investigate multi-criteria trip planning in peer-to-peer shared ride systems.

Three experiments are conducted, according to three types of client preferences: 1) clients prefer the fastest trip; 2) clients consider both travel time and fare; and 3) clients care about travel fare only. The third experiment has a trivial result: in the simulation, walking is always the cheapest way to travel, and the walking time is predictable, too. Therefore, to avoid the trivial case in this experiment, it is assumed that all clients are immobile, but would not mind making detours. Parameters in this experiment are set as before, with a host density in this case of 0.36, and mixed host types.

Multi-criteria optimization is implemented as a k shortest path algorithm [21] for the primary cost criterion, followed by a search for the optimal candidate according to

the secondary cost criterion in this set of k candidates. It is assumed that clients choose travel time as primary, and travel fare as secondary criterion, and k is set to three in this experiment.

Figure 9 presents the three experiments, the bars showing average travel time, and the points connected by a line showing average travel fares. Multi-criteria trip planning (the second experiment) is neither fastest nor cheapest, but relative cheaper and quicker compared to the first and third experiment respectively. The average travel time of the multi-criteria optimization is only slightly above the fastest trip (note that the scales do not start at 0). The average travel fare, however, can be reduced significantly by taking this criterion under consideration as well.

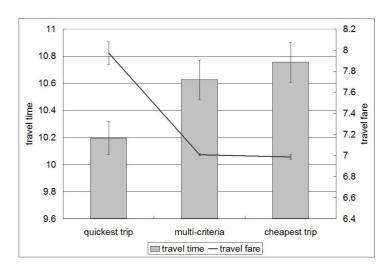


Fig. 9. Comparison of multi-criteria vs. single-criterion trip planning.

7 Conclusions and outlook

This chapter extends the context of geosensor networks—wireless mobile location-aware sensor networks—to an application in the field of transportation. A peer-to-peer shared ride system is presented composed of mobile geosensor nodes, which are either transportation hosts or clients. These nodes have heterogeneous properties, behaviors and interests. Since they are able to communicate over short distances with each other to look for or to provide rides in an ad-hoc manner, nearby nodes collaboratively try to optimize the satisfaction of the individual interests.

This chapter has been developed from previous research of a peer-to-peer shared ride system with an immobile client following a geodesic route, and homogeneous hosts that move on the basis of a random walking model. The previous research was extended by the introduction of mobile and flexible clients, various types of hosts, other agents,

and more realistic mobility models. Finally, the clients were enabled to optimize their trips for multiple criteria.

Reviewing the results, multiple types of agents enrich the choices of clients, which leads to trips of lower costs. The largest impact has a system with mobile and flexible clients and all types of host agents, since it provides the largest choice. Mid-range communication still delivers trips of durations close to those from a (fictional) unconstrained communication range, but has much lower communication costs. Hence, the hypothesis has been proven. Since all experiments were parameterized by the density of hosts, and not by their number, one can expect that the observed results hold for longer trips as well, and also for other forms of street networks.

It is also shown that trips derived from local knowledge (of any communication range) may not be optimal from a global view. Better rides provided by distant hosts and hosts entering the traffic after the client has made a booking are always possible, and can be documented from a subsequent analysis of the simulation protocol. This problem can be approached by more intelligent wayfinding heuristics of the clients. Clients could, for example, learn from experience and use this knowledge in predicting chances of being picked up at specific nodes. For this purpose, a client could exploit a hierarchy in the street network, or known traffic counts at particular intersections, to assess potential transfer points in the trip planning process. This idea is being investigated elsewhere [19].

Although the mobility models used in this chapter are sufficient for the present simulation purposes, they can still be further refined to model more aspects of real traffic flow, such as cycles over the time of the day, or congestions. It is shown, however, that it brings advantages to trip planning if the random walker model is replaced by a more sophisticated mobility model where agents have knowledge of the main streets, and have a preference for using them. Hence, other meaningful improvements of the mobility models, and their consideration by a trip planning agent, are expected to show further advantages for the trip costs.

Multi-criteria optimization is essential for more intelligent wayfinding behavior. For example, clients may be interested to reduce their number of transfers and their trip travel time. The introduction of different fare structures, and the choice of the cheapest trip (or of a balanced cheap trip in a multi-criteria optimization) already tests economic concepts of a peer-to-peer shared ride system. The inclusion of more criteria requires another multi-criteria optimization strategy.

Another future extension of this system comes with admitting other clients into the simulation (*clientNum>*1). Then the passenger capacity of the hosts becomes a critical resource. Clients would compete with each other, which might recommend more booking ahead. But more aggressive booking strategies conflict with the hosts' interests of traveling with occupied vehicles, since travel plans are highly dynamic. Balancing these interests needs to be investigated.

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