SOCIAL NETWORKS IN AGENT-BASED MODELS FOR CARPOOLING

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ABSTRACT

In this paper we present social networks in an agent-based model (ABM) for carpooling. Our model for the carpooling application is a computational model for simulating the interactions of autonomous agents and for analysing the effects of change in factors related to the infrastructure, behaviour and cost. Primarily, we focus on our agent-based approach for creating social networks for the carpooling application using socio-demographic data and daily activity-trip schedules estimated by Feathers, which is an activity-based traffic demand model. Social networks for the carpooling application, called *carpooling SocNet* in this paper, depicts the potential relationship information between carpoolers. We need relationship data to initiate our agent communication model and then employ a route matching algorithm and a utility function to trigger the negotiation process between agents. To generate *carpooling SocNet*, we proposed three similarity measures: profile, path and time interval similarity measure. In order to test the three similarity measures, we conducted experiments with input data in the Hasselt region and Limburg province, Belgium. As a result, it shows an interesting relationship information between the agents, which people in the study area have 65% of similarity to each other based on socio-economic attributes. Moreover, we found it is important to find an optimal value of the threshold because of the impact on finding a carpool partner and dependency on the study area. We plan to, as a part of the future work, use this *carpooling SocNet* data and feed it to our agent-based model to initiate communication, coordination and negotiation in carpooling.

Keywords: agent-based model, activity-based approach, carpooling application, social network, similarity measure

INTRODUCTION

Recently an activity-based approach has been popular and used for establishing new transportation policy and studying social interaction in transportation. The activity-based approach can predict the traffic demand on a (road) network by inducing a daily activity-trip schedule for individuals from observed data. In addition agent-based techniques are being used to support the activity-based traffic demand model in order to assess the effects of individual's (agent) decision-making and the interactions between individuals. An activity-based approach supplemented with an agent-based technique is called an agent-based (micro-simulation) model in this paper.

An agent-based model (ABM) is a class of computational models for simulating the actions and interactions of autonomous agents with a view to assessing their effects on the systems as a whole (*1*). Application of ABM is not only limited to the computer science domain. Currently many research areas including transportation behaviour modelling, need to analyse and model complex phenomena of interactions between different entities. While traditional modelling tools cannot catch the complexity, ABM is able to do it through modelling the interaction of autonomous agents (*2*).

Such a model operates at an individual level with detailed information about an agent's socio-demographic attributes such as gender, age, work status, income and so on. The relationships between agents are also necessary for ABM to study the agents' interaction. However, it is normally difficult to collect and access such kind of data because of privacy protection. Even in rather detailed data sources such as census, there is no detailed information about individual relationship. Therefore, a new method, known as social networks in ABM (*3*), is required to generate the agent relationship. In our paper, we propose ABM with emphasis on creating the social networks (relationship data) for the carpooling application also called *carpooling SocNet* in this paper. The *carpooling SocNet* is required to trigger the further required interactions between agents in ABM.

In this study, we propose a new method for producing *carpooling SocNet* using three similarity measures: profile similarity measure, path similarity measure and time interval similarity measure. The following section introduces research relative to social network in several domains. Section 3 briefly describes background information about ABM, and then section 4 illustrates *carpooling SocNet* and three similarity measures. Next, section 5 explains an experimental setup and some results. Finally, we conclude this paper with discussion and future work.

RELATED WORK

Social networks have been studied in various fields with a different point of view. In computer science, most researchers have conducted morphological approaches to the structure of social networks. Milgram (1967) experimented the first quantitative studies of the structure of social network, and he found the "small-world effect" supporting that six is the average number of acquaintances separating any two persons in the whole world (*4*). Watts and Strogatz (1998) proposed a "random graph" model that is a regular lattice with a degree of randomness for small-world networks. They assumed that the connection topology in social networks is located between completely regular and random in practice (*5*). More recently Hackney and Marchal (2009) developed a social network model considering spatial and temporal dimension. The proposed model is based on a certain probability that people become friends if they remain at the same place in an overlapping time interval (*6*).

Most of related studies in social science can be divided into two categories: egocentric approach and numerical approach. The egocentric approach investigates the influence of social network features on society using survey data which includes information about personal relationship. For instance, according to his survey data, Axhausen (2005) assumed that travel behavior is mainly formed by a personal social network, such as family, friends, and colleagues (*7*). Carrasco et al. (2008) collected personal data on social activity-travel behavior, and then they experimented social networks by travel behavior analysis (*8*). Sunitiyoso et al. (2007) studied influence by investigating environmental awareness, encouraging car-sharing, and mode choice behavior (*1*). Urry (2007) argued that people conduct social activity and travel for being attracted to others and joining in forms of social interactions, based on his experiments (*9*).

On the other hand, the numerical approach generally simulates social phenomena accompanying agent interactions by analyzing social network using spatio-temporal methods. For example, Hägerstand (1970) employed the concept of the space-time prism which is carved out by distance from home (*10*). Bonabeau (2002) and Macal and North (2006) presented a concept of dynamic relationships between agents, and describes how relationships can form and dissolve, and supposed that the topology of the interactions is heterogeneous and complex (*11*, *12*). Timmermans et al. (2002) proved that people travel longer and longer as their potential activity space becomes larger, which is called a time-space theory (*12*). Marchal and Nagel (2005) developed the model incorporating both influence and selection to investigate individual activity locations for shopping and leisure (*14*). More recently Carrasco and Miller (2007) developed a "proof-of-proof" model to study how social activities can be generated from a social network (*15*).

Despite much contribution from former research, there still exist drawbacks and challenges in social network study. First, regarding morphological approaches, studies are limited on virtual cases, for instance friendship in cyber world, so that it is too abstract to be applied to a practical event like carpooling. Secondly, as the egocentric approach is strongly dependent on observed data, it requires a lot of resources to collect data. At last, on numerical approaches, there does not exist a well-defined method to build and/or specify a social network without detailed data so far. In addition, the few existing methods cannot handle big datasets due to rather complicated and heavy mechanisms.

AGENT-BASED MODELING (ABM)

Agent-based modelling is used to simulate agents' interactions. In order to develop an agent-based model, the agents and their environment first need to be defined. In this section, we provide with a basic definition of our agents, a set of activity and interaction rules with respect to the carpooling application. The carpooling procedure consists of several steps; (i) initiate the motive to carpool, (ii) communicate this motive to others, (iii) negotiate a plan with others, (iv) execute the agreed plans and (v) provide a feedback to all concerned. These steps correspond to the requirements of an agent-based model (*16*).

Defining an Agent

In this study, agents are defined as people living in the study area and executing their own daily schedule in order to satisfy their needs. There are two categories of these agents that can either belong to one or both of the categories. The first category is a household member such as the husband, the wife, the parents or the children. The second one is a society member, such as a friend, colleague or neighbour. In this study, we consider socio-demographic attributes including age, gender, income and so on, and individual activity-trip schedule data supplied by Feathers, an activity-based traffic demand model (*17*). The environment is established as the spatiotemporal aggregate where the agents live and conduct their own daily schedule.

Activity Rules for Agents

Agents follow activity rules; (i) goal setting, (ii) scheduling based on a given resource and environment and (iii) conducting the schedule (*16*). In addition, the agents interact with environment in a number of ways. For example, travel time may fluctuate by network condition, travel route can be shifted by construction of new transport facility or cost may change over time due to new policy measures established by the government. Agents react to these changes in the environment by revising activity time or place or by choosing a new transport mode or even consider rescheduling and re-routing. Furthermore, agents communicate with each other in order to sense, manipulate and adapt to any change in the environment. In that sense, our model allows agents to exchange information about trip schedule through message passing.

Agent Interactions for the Carpooling Application

In this section, we present communication and coordination aspects, *carpooling SocNet* and negotiation procedure for the agent-based carpooling application. Initially each agent has a basic set of characteristics such as interests (e.g. carpooling) and requirements (e.g. travel costs, time and route, car capacity or reputation) (*16*).

$$CarpoolPotential(CP_n) = \{Location(L), SpatialRelevant(SR), Interests(I), Requirements(R)\} \quad (1)$$

In order to interact, agents need to reach a given matching level $CarpoolPotential(CP_n)$ as shown in equation (1). $SpatialRelevant(SR)$ denotes the matching between the origin and the destination of all interacting agents. In order to evaluate whether or not agents match the distances between the respective origin and destination locations are used.

Mutual Assessment by Agents

AgentReputation (*AR*) is the reputation of an agent as a carpooling candidate. It will help to perform ‘Outlier Detection’ and ease the decision making process. The reputation value is between 0 and 1 and is either increased or decreased based on the quality of its carpool (*QoC*) feedback (also between 0 and 1). In order to take into account the active participation of an agent in terms of the carpooling experience, we define participation factor (*pf*) as shown in equation (2). In this formula, *i* is number of former interactions between two or more agents for carpooling. We use a logarithmic function to normalize and makes a gradual increase *i* from 0 to 1. The participation factor is directly proportional to the change in *AR*. In this equation, *T* is the reputation threshold.

$$pf = 1 - \frac{log_2(i)+1}{i} \quad (2)$$

$$AR(n)_i = AR(n)_{i-1} + (QoC(m) - T) \times \frac{AR(n)_{i-1} \times pf}{SRDist} \quad (3)$$

where *n* and *m* identify the agent and message, respectively . Messages with a *QoC* feedback value greater than *T* increase *AR* and vice versa. *SRDist* is related to the *SR* factor that helps to reduce the negative effects of feedback from agents having dissimilar paths. In this paper, we will not provide more details about the communication and coordination phase.

carpooling SocNet

While, like social networks in other fields, *carpooling SocNet* is made up of nodes representing individuals and links defined by one or more specific types of interdependency, such as friendship, it slightly differs from general social networks. First, *carpooling SocNet* considers not only socio-demographic attributes but also spatiotemporal attributes, for example activity (or trip) time and location. Secondly, *carpooling SocNet* is specifically aimed at carpool partner selection and interaction between carpooling members.

Negotiation

Negotiation is an important step in an agent-based model. In the negotiation phase we need to take into account the issues over which negotiation takes place, negotiation protocols that will be used and the reasoning model that will be employed. First of all, we considered trip route and time as issues for carpooling. A matched route consists of two terminal nodes (origin and destination) and a series of segments (shortest path between two nodes, either a terminal node or an internal node). In the model, agents negotiate to agree on a deal. Each agent is assumed to have a preference over all possible deals. They want to maximize their own utility but they also face the risk of a break-down in negotiation, or expiration of a deadline for agreement. In this paper, we will not provide more details about this negotiation phase.

SOCIAL NETWORKS FOR CARPOOLING APPLICATION

Carpooling Social network

In this section, we illustrate three measures for generating *carpooling SocNet* using agent's socio-demographic attributes and daily activity-trip schedule. First of all, we set two assumptions with regard to car-pooler's behavioural tendency based on two popular hypothesis, also known as "*Homophily*" (*18*), in psychology and sociology.

I. *The more similar on the background of two persons, the higher the probability of having a relationship with each other*.

II. *The more common on the trip paths in a daily activity-travel schedule, the higher the chance of carpooling together*.

Based on these assumptions, we applied three similarity measures to generate the *carpooling SocNet*: profile, path, and time-interval similarity measure. These similarity measures enable to calculate the degree of similarity between two agents in terms of socio-demographic attributes, activity-trip location and time. Note that this study only considers a commuter carpooling (for home-work trips), not including irregular carpooling or car-sharing (like hitch hiking) and carpooling within a household, because research on such irregular carpooling is too complex to analyze users' behavior and its relationship to socio-demographic characteristics.

Profile Similarity Measure

Profile similarity measure (PFS) is defined by comparing individual social attributes associated with a pair of two agents. Related research efforts (*19*, *20*) have offered several measures for the profile similarity. Among them, the simplest one defines a similarity as 1 if the corresponding attribute values are identical and 0 otherwise. Other more complex measures make use of a continuous distance function based on the values of each attribute. Among several distance functions, the most common one is the Euclidean distance function, which is defined as:

$$Dist_{xy} = \sqrt{\sum_{a=1}^{n} D_a(x_a, y_a)^2} \tag{4}$$

$$D_a(x_a, y_a) = (x_a - y_a) \tag{5}$$

where x and y are two input vectors (profiles) and n is the number of the attributes, a, in the application. However, the Euclidean distance function has a disadvantage that it assigns overpower to the attributes that have a relatively large range. Therefore, the distance needs to be normalized to the range of attributes by dividing the distance for each attribute. We calculate the normalized distance by dividing the difference between two values for attributes as follows:

$$Dist_{xy} = \sqrt{\sum_{a=1}^{n}(ND_a)^2} \quad (6)$$

$$ND_a = \frac{D_a(x,y)}{\max(D_a)} \quad (7)$$

where $\max(D_a)$ is a range of attribute a (i.e., maximum-minimum). Since the distance, $Dist_{xy}$, is arranged to a value from 0 to $\sqrt{n}$, we again normalize it from 0 to 1. Then, we compute the normalized distance between two agent profiles, $Dist'_{xy}$, as follows:

$$Dist'_{xy} = \frac{Dist_{xy}}{\sqrt{n}} \quad (8)$$

One needs to be careful when handling categorical data because a similarity between categorical data is not straightforward due to the fact that there is no clear notion of ordering between categorical values (*19*). Therefore, we redefine the difference, ND, to be able to be applied for the profile similarity of both categorical and non-categorical attributes. We apply a heterogeneous difference, HD, that uses different functions depending on the type of attribute, either categorical such as gender and driver license or non-categorical such as income and age, as follows:

1) If the attribute is categorical,

$$HD = \begin{cases} 0, & \text{if } x = y \\ 1, & \text{otherwise} \end{cases} \quad (9)$$

2) If the attribute is non-categorical, (same as ND)

$$HD = \frac{D(x,y)}{\max(D)} = ND \quad (10)$$

Finally, PFS is defined by the following formula. PFS has a value of 1 if two profiles are identical, but it has less than 1 as a value otherwise.

$$\text{ProFile Similarity (PFS)} = 1 - Dist \quad (11)$$

It is assumed that two agents are unrelated if their PFS is below a given threshold. Since the threshold affects carpool partner matching and may depend on the structure of social network, it is important while producing a social network, to find an optimal value for the threshold.

Path Similarity Measure

As for the path similarity measure (PTS), we compared a pair of trip paths for two agents in terms of the locations involved. Those individual data about trip paths are deduced from a daily activity-trip schedule produced by Feathers. In this study, we only consider trips going to work because such temporally regular activity like working has been shown to influence successful carpooling formation (*21*, *22*). We only compare agents who are adults having a job, for the path similarity method. PTS is used as a proxy for a more sophisticated method based on negotiated routes. Co-routing and negotiation are computationally expensive; hence PTS is used to exclude infeasible cases.

We assume that a carpooling route covers both trip paths for a driver and passenger(s). A carpooling trip first departs from a driver's origin location to a passenger's origin location to pick him/her up, and goes to the passenger's destination to bring him/her to the location. After that, the driver goes to his/her destination. According to this assumption, we compare the distance of an original trip (from an agent's origin to destination) with the distance of a carpooling trip including a trip path for the agent's carpooling partner.

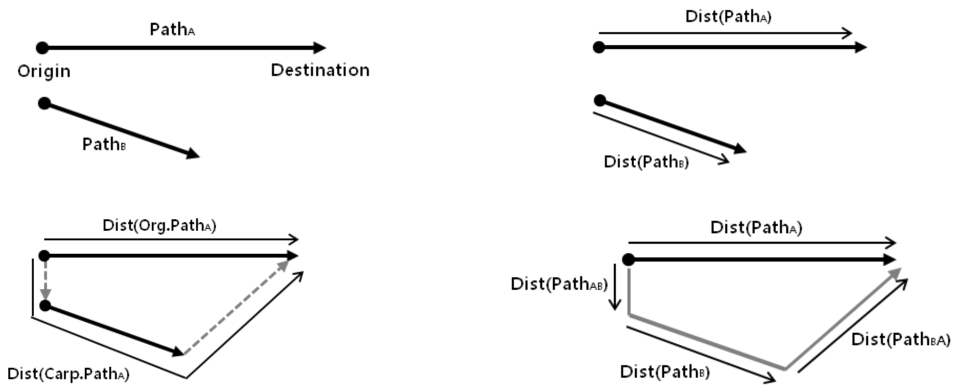

FIGURE 1 Path similarity measure.

Let two trip paths for agent A and B be $Path_A$ and $Path_B$, and the distance of each path be $Dist(Path_A)$ and $\mathrm{Dist(Path_B)}$. Path similarity compares the distance of the original trip path for the agent A, $Dist(Org.Path_A)$, and the distance of a carpooling trip path with the agent B as a carpooling partner, $Dist(Carp.Path_A)$. We need to compute the distance from the agent A's origin to the B's origin, $Dist(Path_{AB})$, and also the distance from the B's destination to the A's destination, $Dist(Path_{BA})$. Therefore, $Dist(Carp.Path_A)$ can be calculated by follows (see also Figure 1):

$$Dist(Carp.Path_A) = Dist(Path_{AB}) + Dist(Path_B) + Dist(Path_{BA}) \tag{12}$$

As a result, PTS is defined as follows:

$$\mathrm{PTS}(A,B) = \frac{Dist(Org.Path_A)}{Dist(Carp.Path_A)} = \frac{Dist(Path_A)}{Dist(Path_{AB})+Dist(Path_B)+Dist(Path_{BA})} \tag{13}$$

where A is the driver. PTS has a value with a range from 0 to 1 according to two distances, $Dist(Org.Path_A)$ and $Dist(Carp.Path_A)$. If PTS is 1, it means that both distances are identical, since two comparing agents have a common trip path, but it has a value with less than 1 otherwise. Note that PTS is not a symmetric relation. When candidate A does not own a car and driver license, then $\mathrm{PTS}(A,B) = 0$.

Time Interval Similarity Measure

Time interval similarity measure (TIS) is a value in [0, 1] assigned to an ordered pair (*pte*0, *pte*1) of *periodicTripEx* that indicates to what extent the time intervals involved are compatible for carpooling (see figure 2). A *periodicTripEx* denotes the weekly execution of a trip with given characteristics by a specific individual.

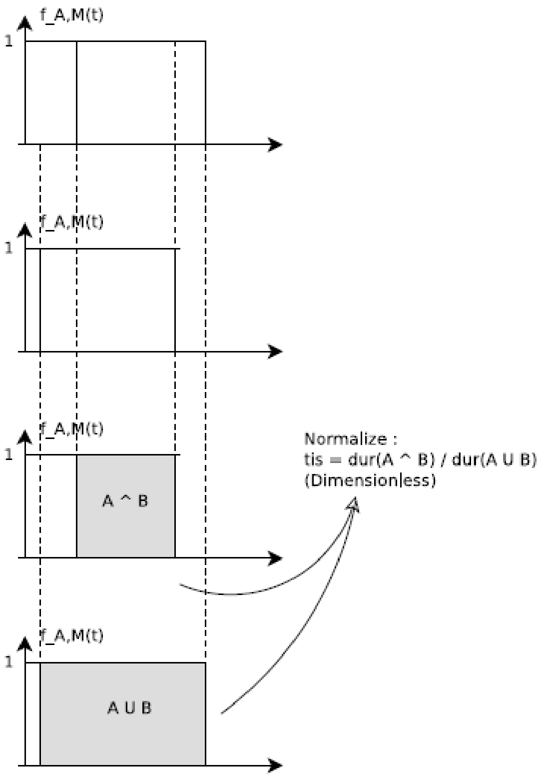

FIGURE 2 Concept of time interval similarity measure.

Each individual specifies the feasible departure and arrival intervals for each trip. Both departure and arrival feasible intervals for the trip are used to determine the similarity. Let *tb,·* and *te,·* denote respectively begin and end times of intervals. Let *pte.id*() and *pte.ia*() denote respectively the departure and arrival intervals of the *periodicTripEx pte*. Following function is proposed:

$$t_{b,max} = \max\left(t_{b,i_0}, t_{b,i_1}\right), \qquad t_{b,min} = \min\left(t_{b,i_0}, t_{b,i_1}\right)$$

$$t_{e,max} = \max\left(t_{e,i_0}, t_{e,i_1}\right), \qquad t_{e,min} = \min\left(t_{e,i_0}, t_{e,i_1}\right)$$

$$tis_{int}(i_0, i_1) = \max\left(0, \frac{t_{e,min} - t_{b,max}}{t_{e,max} - t_{b,min}}\right)$$

$$tis(pte_0, pte_1) = tis_{int}(pte_0.i_d(), pte_1.i_d()) \times tis_{int}(pte_0.i_a(), pte_1.i_a()) \qquad (14)$$

where i_0 and i_1 denote individuals. The function $tis_{int}()$ is an interval overlap measure. TIS is defined as the product of the departure intervals overlap and the arrival intervals overlap. Note that time similarity is defined only for *periodicTripEx* having identical origin and destination; hence in this case the time interval for the passenger origin and destination need to be used.

Carpooling SocNet module for Agent-Based Model

In actual practice, a carpooling participant tends to contact others to find a partner inside his/her social network. Once found, the carpooling participant and partner(s) start negotiation about the detail of the carpooling plan, for example trip path, time and cost. According to the result of negotiation, individual daily activity-trip schedule is more or less adjusted to the confirmed carpooling plan. Based on these typical procedures of carpooling, we use *carpooling SocNet* as a pre-processing module of our agent-based carpooling application being developed. The ABM is used to test the matching service before deployment. The *carpooling SocNet* module is used in both the testing (phase 1 in Figure 3) and operational phases (phase 2 in Figure 3). An ABM is used to test the matching service because training the logit predictor requires a lot of data and thus also time.

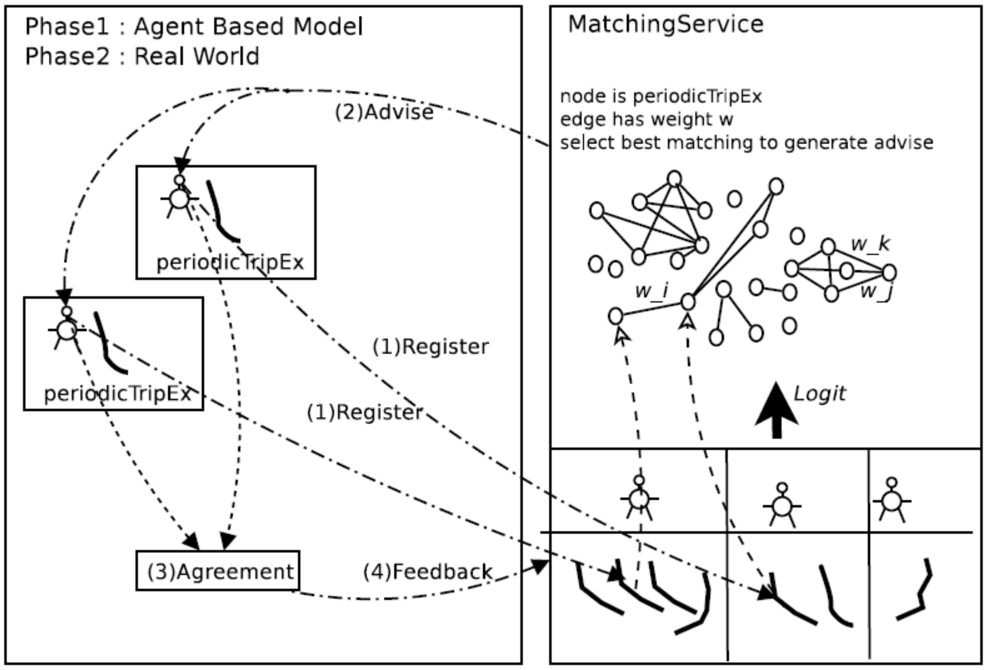

FIGURE 3 Concept of *Carpooling SocNet* module in agent-based model.

The *carpooling SocNet* lifecycle is given below, and the steps from (1) to (4) are repeated forever:

(1) register agents' information about socio-demographic attributes and activity-trip schedule for the *carpooling SocNet* module,

(2) calculate and provide the similarity measures, PFS, PTS and TIS using the agent information,

(3) conduct *periodicTripEx* and simulate agent negotiation according to the given similarity measures,

(4) train a logit with the relationship between the similarity measures and the feedback from the result of the agent negotiation,

(5) and serve a matching service to potential carpoolers in a real-world.

EXPERIMENT

To validate the *carpooling SocNet* module including the three similarity measures we did some experiments using datasets in Hasselt region and Limburg province in Flanders, Belgium (see figure 4). The datasets contain socio-demographic attributes and daily activity-trip schedule data. The socio-demographic data came from a trip-based survey (called *OVG*) in Flanders and was applied to calculate PFS values, and the daily activity-trip schedule was estimated by Feathers (activity-based traffic demand model) and used as spatiotemporal data to calculate PTS and TIS by providing trip location and time.

FIGURE 4 Study area in Flanders, Belgium.

In this study, we used fractional data of the daily activity-trip schedule, so that FRAC_10 and FRAC_100 represent a 10% and 1% of the whole population in the study area, respectively. The experiments were set up as follows:

- a list of zones in a given superZone (e.g. l_{270} of 270 superZone, where is Hasselt region) has been specified
- an individual is added to a carpooler candidates list c_0 if and only if its home and all of its work locations are contained in the specified zones list (e.g. l_{270}).
- Finally two sets, FRAC_10 (including 389 individuals in Hasselt region) and FRAC_100 (including 641 individuals in Limburg province), were selected by uniform random sampling from c_0.
- From the two sets (called FRAC_10 and FRAC_100, respectively), individuals having a job and going to work in the morning (between 8 to 10 hour) have been selected. For each such individual, the first home-work trip has been considered (hence one trip for each person).

For each pair of individuals, PFS and PTS measures have been calculated; a pair was kept if and only if the profile and path similarity exceeded a specified threshold. Thus, the sample average is taken as threshold for PFS, and 25% and 75% percentiles are for PTS. Based on the average value of PFS, we define whether or not two agents shall be considered to be candidate carpooling partners. In other words if PFS is smaller than the threshold, then two agents have no chance to carpool together. On the contrary, if the PFS exceeds the threshold, they are considered to be candidates for carpooling negotiation. As for PTS, 0-25%, 25-75% and 75+% indicates a low, medium and high similarity of trip path for the agent pair, respectively.

The first experiment using FRAC_10 results in a set of 389 individuals. Hence, we found $389^2 - 389 = 150{,}932$ off-diagonal relevant values in three similarity matrices. For the second experiment, a set of 641 individuals are selected from FRAC_100, so we achieved $641^2 - 641 = 410{,}240$ as the number of pair of two agents.

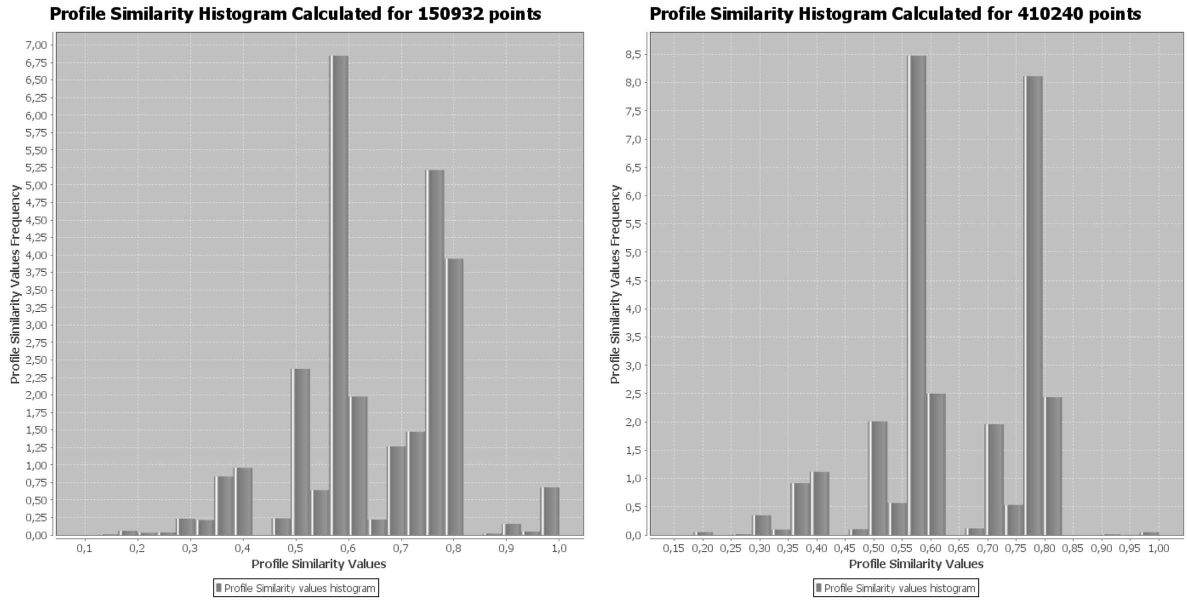

FIGURE 5 Socio-demographic profile similarity measure with distributions for Hasselt region and Limburg province.

Figure 5 illustrates the result of profile similarity measure with distributions for both experiments for Hasselt region and Limburg province. The experiment for Hasselt region shows a two-peaks (approximately 0.6 and 0.8) distribution with around 0.65 average and 0.14 standard deviation on the histogram. Note that the histogram seems to be bimodal: it might came from merging categorical and continuous attributes into one measure. As for the experiment for Limburg province, the histogram shows the similar pattern as for Hasselt region, except more concentrated on the two peak values. According to the result, we can say that a pair of two people randomly chosen in the study area, normally have around 65% of similarity with each other based on their socio-economic attributes.

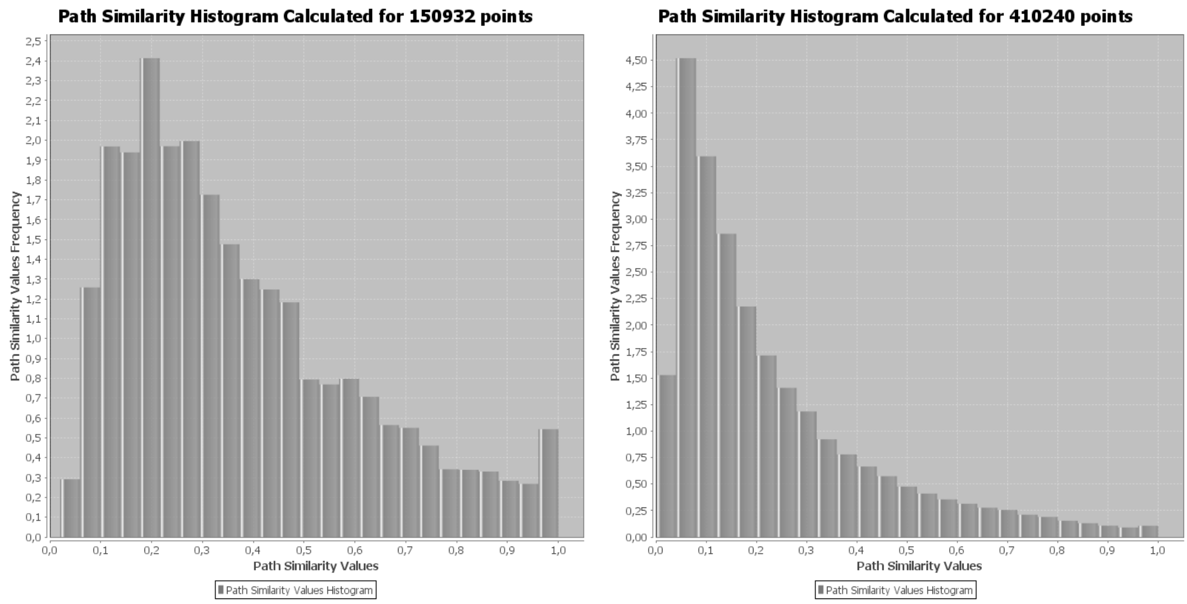

FIGURE 6 Path similarity measure with distributions for Hasselt region and Limburg province.

Figure 6 depicts a path similarity measure with distributions for two experiments for Hasselt region and Limburg province. Note that in figure 6, the histogram resulting from the experiment for Hasselt region shows a downward pattern in most of PTS values with the highest frequency on 0.2. On the other hand, the result of experiment for Limburg province describes a highly concentrated distribution around a lower-value of PTS (around 0.1) though an analogous downward pattern on PTS values. Based on the result, we found that the distribution of PTS is more concentrated on a lower value as the study area becomes larger. This is because a larger area seems to have a lower probability that people share a similar trip path with each other in general. In other words, a difference in trip path for a pair of agents can be bigger or smaller proportional to the size of a study area where the agents belong so that the PTS value is rather small when a study area is big.

Finally, we additionally experimented both PFS and PTS measures for Flanders in Belgium to provide a similarity index of *carpooling SocNet* in the whole study area. Therefore, 0.1% of population data (FRAC_1000) in Flanders was applied for both two measures, and then achieved some results in Figure 7.

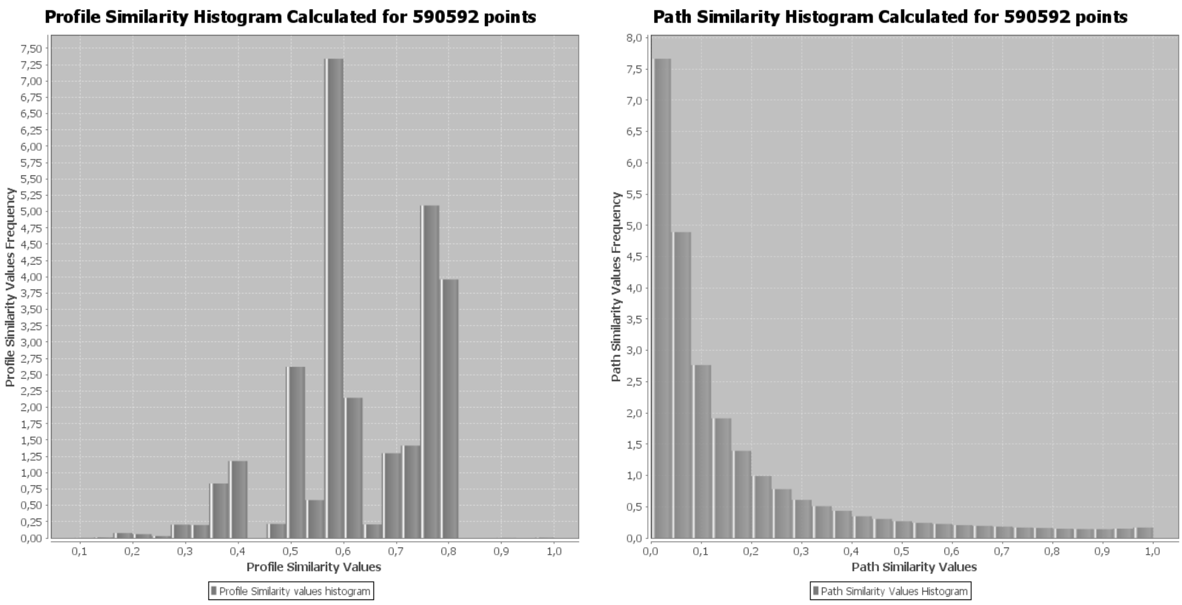

FIGURE 7 Socio-demographic profile similarity and path similarity measure with distributions for Flanders.

Regarding PFS, the general pattern with two peaks is similar with the result of Limburg province and even more similar with Hasselt region. As for PTS, the distribution as a result of Flanders is more concentrated on the lowest value of PTS than two other experiments, because of a larger scale of the area than the others' as mentioned before. To conclude, those measures PFS and PTS reflect a global pattern of similarity in both socio-demographic and spatial aspects according to the result of experiments we did.

CONCLUSIONS AND FUTURE WORK

As agent-based models are becoming popular in the domain of transportation, the detailed information about relationship between agents is increasingly needed for a recent research. Thus, we propose a new method *carpooling SocNet* to produce social networks for carpooling using three similarity measures, PFS, PTS and TIS.

Our similarity measures show interesting behaviours for different data sets as discussed in the previous section. People in the study area generally have around 65% of PFS even with a different spatial scale, Hasselt region, Limburg province and Flanders. Moreover, the distribution of PFS also has a same pattern with two peaks in both spatial scales. Regarding PTS, as the spatial scale of a study area becomes larger, the distribution of PTS is more concentrated on a lower value. This is because a larger area seems to have a lower probability that people share a common trip path with each other in general.

This study suggests a relatively resource-efficient computing and independent method from survey data for producing carpooling candidates networks. Using *carpooling SocNet*, we can apply for simulating agent interaction by providing information about not only similarity of socio-demographic characteristics, but also their trip path and time to the agent-based carpooling application.

On the other hand, this study also leaves some open questions and challenges. First, only a few socio-demographic attributes are applied for the experiments that might be not enough for the application of a real world. Second, when the similarity measures are applied for searching a potential partner in carpooling research, it is crucial to employ a suitable threshold for the similarity measure in a study area. At this time we’re still working on it. Lastly, even if we suggested a new method (similarity measure) for generating social network without requiring relationship input data, the relevance of those measures in the scope of carpooling has not yet been proven. Therefore, a validation study using survey data should be conducted in our future research to feed the development of an agent-based carpooling application. Finally, we plan to integrate *carpooling SocNet* as a pre-processing module into the agent-based carpooling application that we are working on at this moment.

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