Towards a simulation of minibuses in South Africa

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Abstract
After private cars, minibus taxis are the most common transport mode in South Africa. Especially for low-income citizens – living in townships – minibus services are often the only possibility of mobility. Despite the great importance of the mode, the knowledge on routes, fares, and the number of minibuses is very little. Hence it is difficult to simulate and to understand the influence of this mode on other modes and on transport planning in general. This article presents a first implementation to create a "close-to-reality" minibus supply based on demand and street-network only. The approach adopts the survival of the fittest principle using a co-evolutionary algorithm which is integrated into a microscopic multi-agent simulation framework. The successful application to a large scale real-world scenario of the Nelson Mandela Bay Area Municipality in South Africa shows that the approach is able to identify the main minibus corridors as well as to find a robust service coverage in lower demand areas. The resulting minibus supply can then be used to for planning purposes, e.g. to investigate aspects of strategic, operational, or regulatory changes.

Keywords
Multi agent simulation; Demand responsive; Paratransit; Minibus; Jitney; Complex system; Evolutionary algorithm; Public Transport; MATSim; Nelson Mandela Bay; Port Elizabeth

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1 Introduction

The term paratransit has two meanings when referring to transport. One describes a kind of transport specially fitted to the needs of elderly or physically handicapped people. This paper, however, deals with the second meaning: a spatio-temporally flexible mode of transport ranging from taxis up to bus lines (Roos and Alschuler, 1975). That is where either the routes (space) or schedule (time), or both, are flexible. Formal transit would typically have fixed routes with fixed schedules. On the other end of the spectrum, dial-a-ride services are flexible in both their routes and schedules. In most cases, this is a user-demand-oriented mode of transport mainly used in cities of the developing world. Although paratransit shares some underlying principles, it can be distinguished from demand responsive transit (DRT) systems by the way organization takes place. DRT systems heavily rely on a supervising level (controller), such as an agency or government authority, that allocates vehicles to individual trips or collective rides (e.g. ENEA, 2004; Jokinen et al., 2011).

Many paratransit services are complementary to the scheduled public transport. According to Cervero (2000), in most instances, paratransit services compete with rather than complement formal bus and rail services. This happens because paratransit usually emerges and evolves when no or limited formal transit is provided by the relevant government.

In South Africa, as in many developing economies, paratransit takes the form of mini- and midibuses that are privately owned and provide communal transit services along semi-structured routes. Commuters often hail the vehicles along the route as there is seldom a formal stop infrastructure. The services also do not follow fixed schedules. Such a service — minibuses with fixed routes but without fixed schedule — is often called a *jitney* service. This paper will use the term ‘minibus service’, and refer to the operator as a ‘minibus operator’ with the understanding that the jitney/minibus service is one out of many possible paratransit services.

The lack of routes and schedules often creates a semi-chaotic perception of the mode, resulting in the mode being viewed as a necessary nuisance that should rather be formalized. Especially in developing countries paratransit remains largely unregulated often resulting in factions within the industry fighting, literally, over lucrative routes.

In the absence of documented routes and schedules it becomes very difficult, if not impossible, to include such a mode into planning models. Rather, it is dealt with qualitatively in an after-the-fact manner. When transport planners are faced with developing decision-support tools, it is often justified to omit the paratransit since it makes up a very small percentage of the total road user population. In a country like South Africa, however, paratransit is the dominant mode of transport when all trip purposes are considered. Omitting it from formal planning would render the planning model inadequate for comprehensive and inclusive decision-making. The main challenge so far has been the inability of equilibrium assignment models and activity-based planning tools to cater for the dynamic mode that is paratransit.

To our knowledge, this paper presents the first (behaviorally rich) implementation of the dynamic and evolutionary nature of jitney-like paratransit services in a 'formal', large-scale transport model. To achieve this, we extend and build on an existing large-scale agent-based transport model in South Africa. More specifically, we employ the autonomous nature of agents to emulate the unique decision-making process inherent in the minibus industry, and introduce new agents to represent the different stakeholders. Transport planners can then consider to conduct policy analyses using the model.

The structure of this paper is as follows: the next section will give a short introduction to the jitney-like minibus system. Although the case of South Africa will be used, it is extendible to many developing countries. Section 3 describes the proposed minibus taxi model, and how it is incorporated into the agent-based setting. The model is then applied to a large-scale scenario covering the Nelson Mandela Bay Municipality (NMBM) in Section 4. The paper concludes with an analysis of the scenario's outcomes and an outlook for the model and possible further improvements.

2 The minibus industry in South Africa

For a more international discussion on paratransit in various developing countries, the interested reader is referred to Cervero and Golub (2007). In this section we provide a more focused discussion on the South African case. The literature on the minibus mode is quite sparse, and includes early works by McCaul (1990), Pirie (1992), Khosa (1994), and Dugard (1996, 2001).

One of the legacies of the former *Apartheid* regime in South Africa that is still evident today, is the location of informal and semi-formal townships on the periphery of cities and towns. These settlements are mainly occupied by low-income citizens who generally cannot afford private vehicles for their daily commute.

In the absence of reliable formal transit provided by the Apartheid government, the minibus industry has emerged as the dominant mode of transit to serve the poor, mainly black peripheral townships. Over the past three decades it has evolved to account for three quarters of all transit trips. An entire minibus industry emerged over time and forms part of what is colloquially known in South Africa as the *second economy*: a cash-based, unsubsidized industry that is fairly self-regulatory with very little documented in terms of fare structures, routes or schedules — the latter not really existing at all.

For a detailed background of the rise of the minibus taxi industry, as it is known in South Africa, the reader is referred to Joubert (2013). Suffice to say that a loophole in legislation allowed a driver to transport up to eight passengers, for gain, before being classified as a *bus*, which in turn required much more stringent regulations and operating licenses.

When considering only work-related trips, the minibus is only rivaled by private car. Considering all trip purposes, however, it even exceeds private car. Unfortunately, the mode is in direct competition with formal (subsidized) transit provided by the government. There are two types of competition. First, there is the head-to-head competition with conventional public transport buses along popular routes, effectively duplicating the routes. Minibuses arrive at the stop just before the conventional bus taking away passengers by offering a faster trip, albeit more expensive. Second, there is the complementing type of competition. This happens if headways of the fixed-schedule bus are too long and the minibus fills in the gap, shortening the effective waiting time. For a more comprehensive description of the characteristics and underlying principles of paratransit systems, and minibuses in particular, the reader is referred to Neumann and Nagel (2012).

2.1 The industry structure

Although it was common during the 1980s for drivers to own their vehicles, most minibus drivers nowadays are employed by the vehicle owners. Owners have organised themselves into associations who, in turn, nominate representatives to the provincial and national councils. The South African National TAxi COuncil (SANTACO) has long been the single body with whom the government now interacts. But as argued by Woolf and Joubert (2013) the minibus industry remains a heterogeneous grassroots operation, as opposed to a homogeneous body as it is often perceived. The industry's amorphous structure has contributed to the popular public view that paratransit, in its current form, should rather be formalized. To this extent, Schalekamp and Behrens (2010) and Venter (2011) review the unsuccessful attempts by government to get a tighter handle on the industry.

For the purpose of this paper it is necessary to elaborate more on some of the key stakeholders in the industry, and the context within which they operate daily.

Associations Taxi associations form when taxi owners serving a similar geographic region organize themselves to protect their routes. Route operating permits are issued by the provincial governments, and the permits only vaguely describe the routes based on its origin and destination rank (terminal). It is up to the associations to negotiate their respective "turfs" amongst themselves. Conflicts often arise between associations when there is an overlap between the 'agreed' operating areas. This typically happens when the ranks of local and long-distance services coincide, and especially when independent drivers provide services without association approvals. The latter are referred to as *pirate taxis* and remain a headache for the minibus industry.

Owners Minibus owners, knowing their operating routes, would roughly calculate an expected daily income, referred to as the *check-in* amount. It then becomes the goal of the driver to earn the check-in amount for the owner. Any additional income would then be for the driver's own pocket.

If an owner manages its business well, it may be capable and choose to extend its business by acquiring more vehicles. First, it must acquire a valid operating license from an association. Finding a driver for the vehicle is much less of a problem in a country with unemployment in excess of 25%. Irregularities in the issuing of operating licenses mean that even in the presence of a moratorium, new licenses are still being issued. As a result, there is usually an oversupply of minibuses in the system, and if the business of an owner is not successful, the owner may eventually pull out and sell one or more of his/her vehicles.

Drivers Minibus drivers earn income from fixed, route-based fares. That is, the fare for a trip from the origin to the destination is set and does not depend on where along the route the passenger boards or alights. About 60% of all boarding and alighting happens along the route. From the fares earned, the driver is responsible for all fuel expenses and fines (a regular occurrence), while the owner is responsible for vehicle maintenance. Once the morning peak demand is over, the majority of drivers will seize service as it incurs costs without yielding certain income. Drivers will typically park around the busy rank areas, and as demand increases again in the afternoon, services resume.

Fares Fares are usually calculated to cover the expenses of a complete journey. That is, regardless if a passenger enters a vehicle close to the origin or the destination, the fare charged is always the same. An example for that is given by the Transport Plan of Johannesburg (City of Johannesburg, 2004, p.99). However, the fares mentioned in the

Transport Plan differ seriously from the authors' personal experience. For example, in August 2013, a short trip to Pretoria Central of 4 kilometers may cost ZAR 14 (South African Rand, equivalent to approximately EUR 1.06 in August 2013), even though commuters starting their journey at the origin, Mamelodi, which is 25 kilometers away, also pay ZAR 14. Fares calculated on the basis of the numbers derived from the Transport Plan account to ZAR 2.6 for the short and ZAR 4.0 for the longer trip.

Commuters Since routes are not documented, commuters require tacit knowledge of how to navigate the network. This knowledge is acquired through word-of-mouth. In the absence of formal stops, and with the minibuses not being signed in terms of their routes, commuters use an intricate and location-dependent set of hand signals to hail a taxi (Woolf and Joubert, 2013). The hand sign indicates to an approaching taxi what the commuter's desired destination is. If it coincides with the driver's destination, agreed route, and capacity permitting, the driver will stop for the commuter to board.

3 Model description

The model used in this paper enhances the multi-agent simulation MATSim (2013) by a more sophisticated version of the minibus model used in Neumann and Nagel (2012, 2013). In contrast to demand responsive transport systems (DRT), which tend to find a system optimum because the services are cooperating and thus, solve one system-wide instance (Cortés, 2003; Pagés et al., 2006; Fernandez et al., 2008), each operator in this model evolves according to its own optimization procedure. This is related to co-evolution and evolutionary game theory (e.g. Palmer et al., 1994; Arthur, 1994; Hofbauer and Sigmund, 1998; Drossel, 2001). Synthetic *minibus operators* increase or decrease their service frequencies by adding or removing vehicles, depending on each individual line's *fitness*. When no vehicle is left for a *line*, the *line* dies out. In this paper, the focus lies on the enhancements of the minibus network and only a brief overview of the software tool MATSim is given. For a in-depth description of MATSim the reader is referred to Balmer et al. (2005) or Raney and Nagel (2006). The public transport capabilities of MATSim are described in general in Rieser and Nagel (2009) and Rieser (2010), and with focus on its application in Neumann and Nagel (2010).

3.1 A brief overview of MATSim

In MATSim, travellers of the real system are represented by individual agents. Agents typically have several plans that encode among other things their desired activities during a typical day as well as the transportation mode per leg. Currently, private car and public transport are physically simulated. Other modes are not physically simulated, i.e. the travel time of one leg depends on the beeline distance and an average speed only. At each time of the simulation, only one plan is selected for execution. Agents can react to their synthetic reality (traffic flow simulation) through an iterative loop that has three steps:

- Traffic flow simulation: All selected plans are simultaneously executed in the simulation of the physical system.
- Scoring: All executed plans are scored by a utility function.
- Learning: Some agents are allowed to modify their plan in different degrees of freedom. In terms of this work only the search for new routes is allowed.

The physical simulation of MATSim executes the selected plan of each agent. Since all agents compete for the same limited resources, the execution may deviate from the intended plan. For example, an agent can be stuck in a traffic jam, so that it will arrive late at its next activity. In case of public transport, drivers also try to follow their plan and compete with other agents/drivers on the road network. Agents desiring to use the public transport as passenger will have to wait for the next departure, if the vehicle passing by has no capacity left. If there is no further departure the agent is stuck, too.

All executed plans are evaluated by a utility function which in this paper encodes the perception of travel time for the modes car, train, bus, minibus, and walk. For minibus users, the utility function also accounts for waiting, access, egress times, and line switch.

3.2 The minibus model

The *minibus service* is implemented as a part of the public transport system of MATSim (Rieser, 2010). Thus, minibuses face the same restrictions derived from the network, i.e. allowed speed and capacity constrains, as other public transport vehicles and private cars. Minibuses are delayed by a) other vehicles regardless of the type, and b) boarding and alighting passengers. Due to a lack of data on origins, destinations and the actual routes served an evolutionary algorithm is used to create the minibus network from scratch.

At the beginning, each *minibus operator* starts with one *line* which serves one circular *route*/*minibus service*. The *route* is determined by two randomly picked stops and the fastest path in an empty network connecting both stops. The random draw for a stop is weighted by the number of activities in its proximity in order to attract newly found operators to those more promising areas. Initially, this first *route* is operated from a randomly picked start time to a randomly picked end time. The initial number of *minibus operators* and the number of minibuses per operator (serving the first *route*) can be configured.

In spite of reality, minibuses are assumed to run without breaks during their time of operation and will depart immediately after arriving at their terminus. Minibuses are allowed to pick up passengers at every intersection. Minibuses can overtake each other and other public transport vehicles at stops. A minibus fully loaded will not try to pick-up additional passengers and instead proceed as fast as possible to the next stop determined by one of the passengers' desire to alight. A minibus with empty seats left will ask the waiting agents at each stop on its route if they want to enter. The questioned agent will enter the vehicle when:

- The vehicle is running on the correct mode, i.e. an agent planning to board a bus will not enter a minibus.
- The vehicle is serving the desired destination/stop.
- The offered travel time is less or equal than the agent's planned travel time.

Thus, agents are not forced to use planned *routes*, but forced to use *routes* heading them towards their destination within an acceptable time.

Due to the evolution of the minibus system, an adjustable set of agents will be allowed to find new *routes* after each iteration. For that an independent instance of MATSim's current public transit passenger router (Rieser and Nagel, 2009; Rieser, 2010) is used. In contrast to Neumann and Nagel (2012, 2013), agents are only allowed to search for a new route within the mode they already had in their initial plan. The router searches the time-minimizing connection for each agent using the corresponding mode with respect to access and egress walks, waiting time and transfers. The fare calculation is omitted in the route searching due to a lack of detailed information on fares especially for minibuses.

In spite of the different behavior of minibuses compared to formal public transport, the route planning by the passenger is similar to a schedule-based transit assignment. Agents include minibus trips in their plan assuming there will be a certain minibus at a certain stop at a certain time. Especially with minibuses ignoring the timing of their schedule and driving as fast as possible, the minibus may be far away from its schedule. However, for South African minibus services running at high frequencies, this is not a serious issue since the agent will just take the first approaching minibus heading to the desired destination.

3.3 Scoring of the minibus operators

The operator scoring in this paper is the same as used in Neumann and Nagel (2013). At the end of each day (iteration) the operator calculates the revenue generated by each of its *routes* and the expenses related to these *routes*. Revenue is generated by collecting fares. The fare system allows for lump sums, distance-based fares and combinations of both. Expenses consist of fixed costs and distance based costs. Fixed costs cover expenses related to the vehicle, e.g. official operating license and driver. Distance based costs, e.g. fuel, are summed up for each kilometer traveled by the operator's vehicles.

The total score of one operator/*line* can be seen as the operator's (net) cash flow. Profitable operators end up with a positive cash flow, non-profitable *lines* with a negative cash flow. At the end of the iteration, the cash flow is added to the budget of the operator.

3.4 Optimization process

Since a minibus *line* is operated by one operator, each operator tries to improve its own *line*. There is no explicit coordination or cooperation between the operators, except for the fact that an agent using minibus can transfer to a different minibus *line* or *route*. Different operators together can thus form a hub if this emerges from the optimization process, but otherwise are engaged in competition (e.g. Axelrod, 1984). If two different operators ply a similar route, the operator providing a slightly better route, e.g. without additional transfers in between, can oust the other one from the market.

Minibus operators optimize their services in parallel with the agents' adaptation process. In every iteration, the following happens:

1. The operators modify their *routes* as described below and publish their (pseudo-) schedule valid for the current iteration.

2. A randomly selected set of agents obtains a new *route* based on that (pseudo-) schedule, computed as described earlier. The other agents remain on their existing route for this iteration.

3. The traffic flow simulation is run with those minibus operators and passenger agents.

That is, for the present paper the passengers do not optimize beyond what is described in item 2. This means that they do, in fact, not react to the *actual* schedule, or to congestion including denied boarding. Opening more degrees of freedom for the agents replanning is problematic as a) the available data (e.g. fares) is rather sparse, b) the interaction between operator and traveler becomes more complex and unpredictable, and c) the decision which mode is used is based on intrinsic motivation which has not been parameterized, yet.

At the beginning of each optimization step, operators balance their budget to zero by selling or buying minibuses. An operator not able to balance its budget is shut down and another one is initialized. Since the budget depends on the profit of a *line*, the number of minibuses owned by an operator should fit the market restrictions, i.e. the cash flow is balanced and the number of minibuses becomes stable.

If the operator is not shut down, it can further try to optimize its current *line*. The operator chooses one of his existing *routes* by using a random draw based on the number of minibuses serving that *route*, copies the drawn *route* and alters one of the following *route's* attributes:

The time of operation An operator can increase the time of operation by changing the time of the first or the last planned departure. Alternatively, an operator can decrease the time of operation by analyzing the demand of the last iteration. The start time is then set to the time of the first passenger boarding one of his minibuses and the end time is set to last passenger alighting. This can compensate for slack periods, minimizing the expenses of empty minibuses circulating.

The actual stops served by the route An operator can decide to serve an additional stop. This additional stop will be drawn from a set of unserved stops within a specified distance/area around the existing *route*. Now the chosen stop can be added before the first stop, or injected in-between the two nearest existing stops of the *route*. Similar to the reduction of the time of operation, the operator can analyze the demand flow of the stops served. Stops not generating enough revenue to cover their related costs can then be discarded. The remaining stops form the new *route*.

Since operators assess their *routes* by calculating individual *scores* for each *route*, they know which *routes* add most to the success of the *line* and which ones burn money. At the end of the optimization, operators can shift minibuses from less profitable *routes* to more profitable ones. A *route* with the last minibus shifted away will immediately cease operation and is removed. More minibuses serving a *route* directly translate into a higher frequency of that *route*. Eventually, each *route* of an operator has a similar *score* per minibus. Thus, the number of minibuses on a *route* represents the importance of that

Table 1: Characteristics of the generated population and the used sample.

	Complete population	1 % Sample
Persons [#]	1,164,150	11,498
Share of Females [%]	52.5	52.2
Share of Males [%]	47.5	47.8
Average Age [years]	27.7	27.1
Car-trips [#]	356,208	3,574
Minibus-trips [#]	920,722	9,261

route to the operator and thus, give a good estimate for deciding which *routes* to improve further.

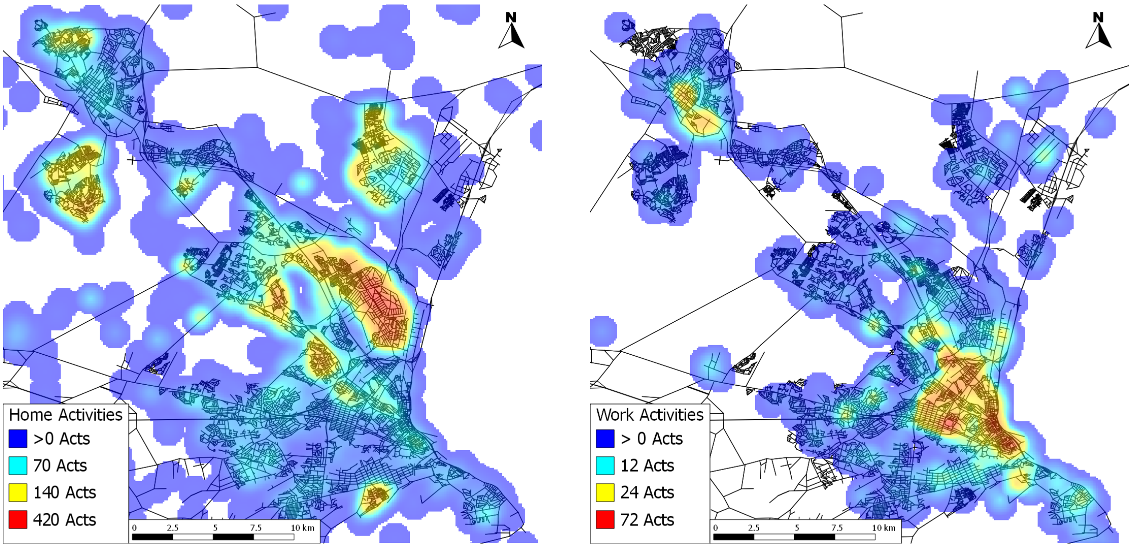
4 Scenario

The synthetic population used in the simulation of the NMBM is generated using two steps. Firstly, we use iterative proportional fitting (IPF), similar to the implementation by Müller and Axhausen (2011). Using the Census 2001 population as source data, the synthetic population is fitted on both household and individual level.

Secondly, travel demand for the population is based on the 2004 travel survey that includes a 24-hour trip diary, covering approximately 1% of the population. For each household surveyed a questionnaire was completed that covered general household information such as number of persons in the household, employment status of the household members, number of cars available, and overall household income. For each member of the household, individual travel information was gathered, among which was a detailed description of the individual's activity chain for the day. Each activity was described using a predetermined activity type, start and end time, as well as the mode connecting the different activities in the chain.

Every individual in the synthetic population is assigned an activity chain sampled from the survey chains. The sampling ensures that the chain is from an observed individual with similar characteristics in terms of employment status, household size, age, and household income. From all households a 1 %-sample is randomly drawn whose members form up the synthetic population for this scenario. The complete synthetic population and the 1 % sample of it are characterized in Table 1.

Figure 1 shows the distribution of activities within the NMBM and the high spatial diversification of home-locations (Figure 1a) and working places (Figure 1b). The home-



(a) Distribution of home activities

(b) Distribution of working activities

Figure 1: Heatmaps showing the distribution of home and work activities.

locations are mainly located in Kwazakele, Zwide, New Brighton, Gelvandale, Westend and Kwanobuhle. The working places are mainly located in the city centre between N2, Cape Road and Settlers highway and in “Alexander Park Industrial” in Uitenhage (north) where the Volkswagen South Africa assembly plant, among other large production facilities, is located.

The network is generated from OpenStreetMap (2012) data and contains 39,507 links.

The model is initialized with 35 *minibus operators* each with an initial fleet-size of 21 minibuses. Since the underlying traffic flow simulation simulates only whole passengers, the typical South African minibus capacity of 16 passengers cannot be reduced to 1 %, i.e. 0.16 passengers. Instead, the capacity is set to 2 passengers per minibus. While this exceeds the actual capacity of a “1%-minibus” it allows to simulate loads different from *completely empty* and *no capacity left*. *Operators* are allowed to buy new minibuses for a price of 1,000 monetary units. They can sell minibuses for 250 monetary units each. Operating a minibus costs the *operator* 10 monetary units per day/iteration and 0.25 per km. Operators earn 3 monetary units per passenger entering a minibus, irrespective of the distance the passenger travels. Note, as shown in section 2 fares are fairly unknown. Thus, the fare-structure for the experiments was choosen to deliver reliable results in terms of passenger flows and route-structure. Newly found operators have 4 iterations to break even. Operators are allowed to create new *routes* until the end of iteration 150. Buying and selling vehicles is allowed until the simulation ends. Minibus stops are located on all links with a speed limit of 80 km/h or below.

In contrast to other applications of the minibus model (e.g. Neumann and Nagel, 2013), we omit the physical simulation of formal public transport due to a lack of consistent data. Thus, only cars and minibuses are physically simulated.

Passenger agents have three plans in their choice-set. In each iteration up to the end of iteration 200, a randomly chosen set of 40 % of the agents is allowed to search for an alternative route within their transport mode. Agents will then stick to that route for the following iterations until they are selected for rerouting again. Based on the authors' experience, transferring to a different minibus results in an additional waiting time because the next vehicle will only depart until it is fully loaded. Since, in the model, vehicles depart immediately, the delay is simulated within the router by setting the penalty for a line switch to an additional 30 min of travel time.

We test for convergence of the system by the same standards as in Neumann and Nagel (2012, 2013), i.e. we analyze the number of trips performed, the number of minibuses put into service, and the average score of the population.

5 Results

In the beginning of the simulation, there is only a randomly drawn minibus-supply. As expected, this supply is neither able to serve the existing demand nor does it fit the real system (as far as information is available). Thus, a large number of agents will be late or even never reach their destination. One might notice two effects for the agents' departures (Figure 2a) and arrivals (Figure 2b). Firstly, both numbers increase over the iterations with a declining effect in higher iterations, especially iteration 150 onwards. This results from the fact that the evolution of the minibus-system is reduced to the capability of buying and selling vehicles.

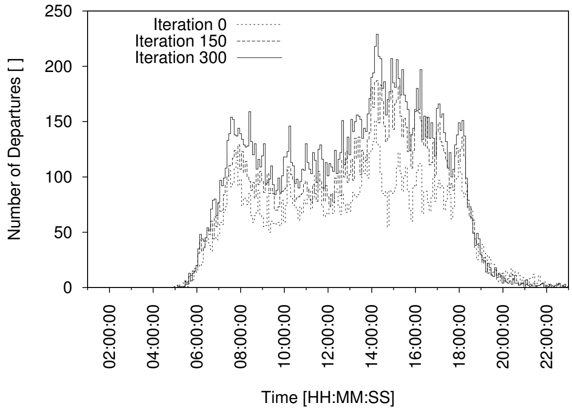
Secondly, the histogram shifts from the right to the left towards earlier departures and arrivals. This effect might be much more clearly noticed viewing Figure 2c, showing the agents "en route". In the very first iteration 0, approximately 830 agents do not reach their planned destination. This results from spillover effects induced by all agents choosing the best option from the schedule. In iteration 150, the number of agents stuck decreases to approximately 350 due to operators adapting to the supply by putting more minibuses into service and thus, increasing the overall system's capacity. Due to the highly competitive minibus market with operators becoming bankrupt and the foundation of new operators an agent's current plan might not reflect the latest changes in the minibus network and thus, be invalid. At the final iteration 300, exactly 191 agents are left who never reach their destination. The majority, 169 agents, tries to use a minibus-*route* that does not exist anymore, i.e. the *route* has been dropped by the operator. The remaining agents miss the last minibus' departure (13) or could not be served, because all minibuses passing by were fully occupied (9). As noted earlier, within the last 100 iterations, operators can only change the capacity of their *routes* by reallocating vehicles or by dropping *routes* entirely. A *route* is dropped in case the operator regards it as unprofitable, e.g. due to insufficient demand. If an agent's choice-set contains only dropped *routes*, that agent will inevitably stuck. That is, the minibus model can not guarantee operators serving all of the population. Instead, operators serve as much of the population as they can afford.

5.1 Minibus service coverage

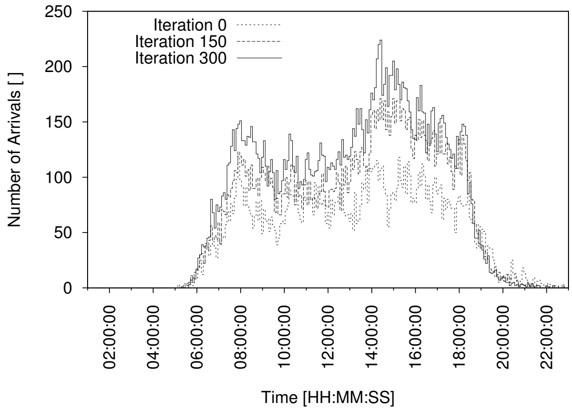
As illustrated in Figure 3, the majority of the urban area has access to the minibus services within a walking distance of less than 500 m. Passengers travelling to or from areas with a low density of activities need to accept longer walking distances to and from the minibus system, compare Figure 1. Note, that for South African cities access trips of up to 2.5 km are considered to be not unusual. For example, figures from the Department of Transport (DoT, 2005, p. 38)) state that about 74 % of the households have access to minibus/taxi-services within 15 minutes of walking, and an additional 13 % of all households can access a minibus/taxi-service within 15 to 30 minutes.

To test for the sensitivity of the model, two additional runs of the same scenario with the same configuration but a different random seed are conducted. Their resulting catchment areas (smaller figures shown in Figure 3) show a similar level of accessibility with only minor differences in low-demand areas. Especially, high-density remote areas like the Walmer-Township or Khaya Mnandi are covered in all three scenarios with walking distances of less than 500 m.

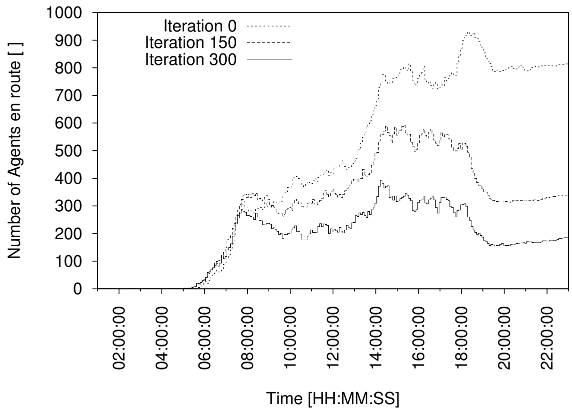
The analysis of access walks from the home location to the minibus system shows that over 85 % of the minibus users walk less than 1,000 m to access the system, see Figure 4. This roughly matches the sparse data available from the "South African National Household Travel Survey" (DoT, 2005) for a "typical metropolitan area" in South Africa. The travel time data included in the survey is transformed in distance classes assuming an average walking speed of 4 km/h. The authors are not aware of any data sets describing the area of the NMBM in particular. However, the simulation results fit the data available for a distance of 2,000 m, and only marginally overestimate the accessibility for a distance of 1,000 m. Overall, the deviations are regarded as negligible.



(a) Number of departures of agents



(b) Number of arrivals of agents



(c) Number of agents en route

Figure 2: Leg-Histogramm-Evolution of the taxi-system.

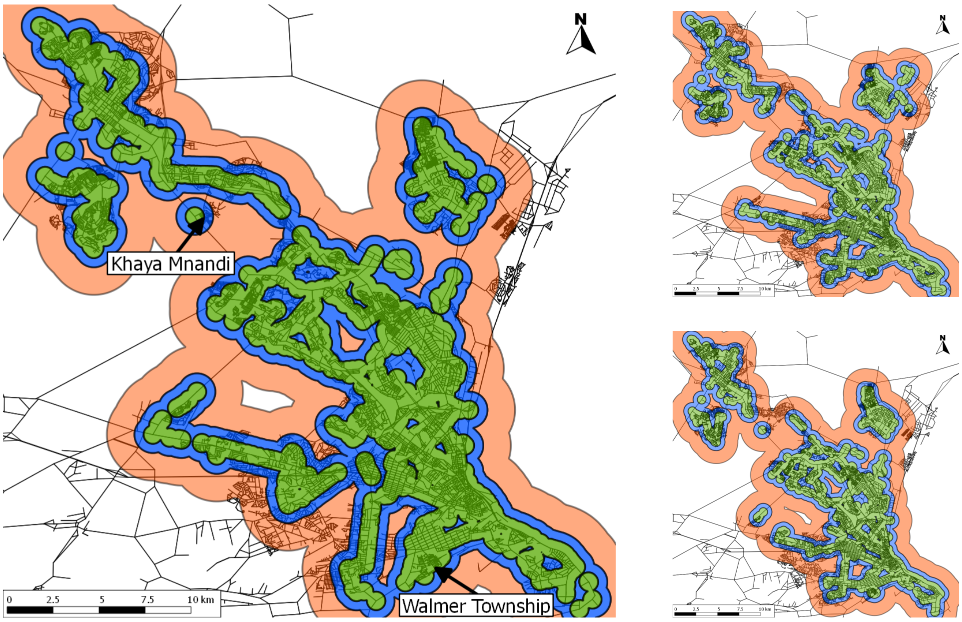


Figure 3: The minibus services' catchment area of less than 500 m (green), 1,000 m (blue) and 2,500 m (orange). The smaller figures show results from sensitivity runs.

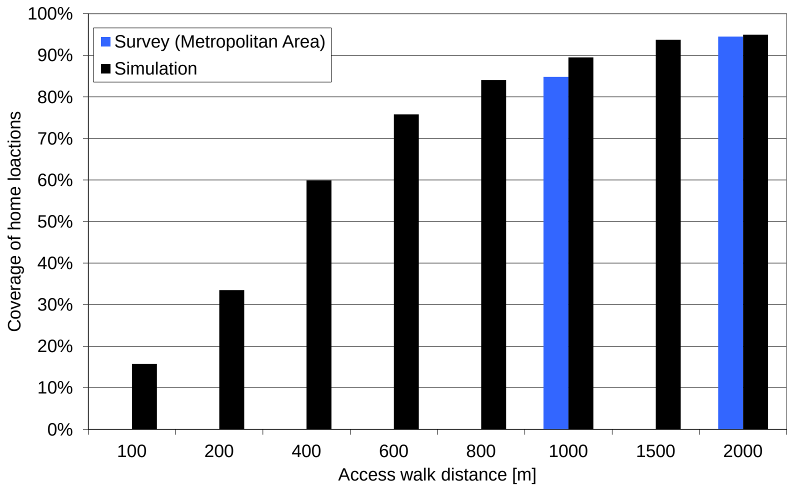
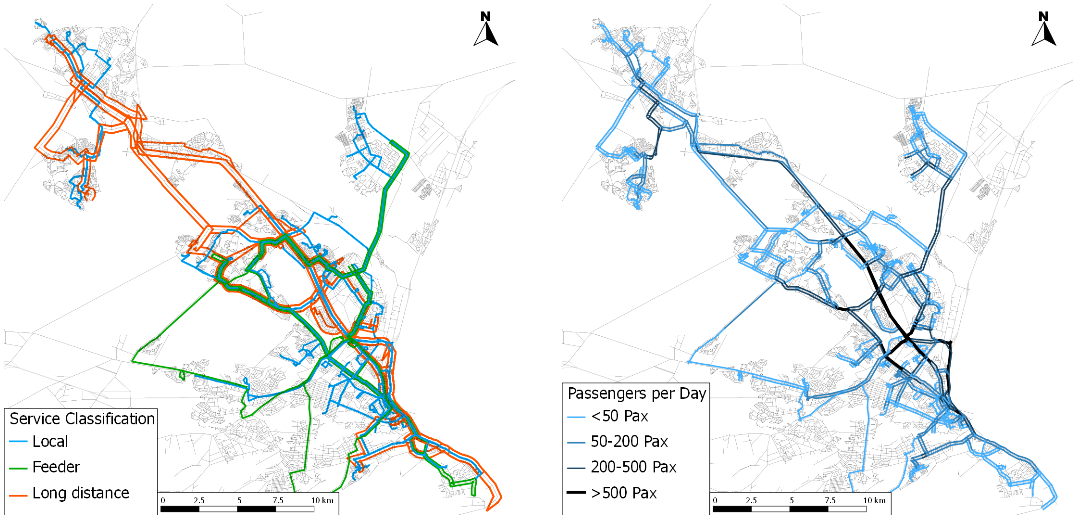


Figure 4: Minibus service access walk distance distribution from home locations.



(a) Lines operated

(b) Passenger volumes

Figure 5: The final minibus system.

5.2 Minibus corridors and passenger volumes

The final minibus network consists of 87 *routes* operated by 25 individual operators. Operators can be classified according to the type of service they provide. The classification shown in Figure 5a distinguishes between local operators accessing neighborhoods though a dense (ramified) network, feeder lines providing service from nearby townships to the city's center, and long distance services connecting the north-western part of the research area (Kwa Nobuhle, Uitenhage) to the city. Since the *routes* of all operators can overlap each other, the sum of all *routes* forms the minibus network. Especially from the point of view of the simulated passenger, it does not matter to which type of service a minibus belongs as long as it has capacity left and serves the destination the passenger asks for. Thus, the minibuses and *routes* of different operators form a combined minibus service. In consequence, trunk roads with multiple *routes* each running at a high frequency serve a higher quality due to a more frequent service and a higher probability to the passenger to be picked up. Figure 5b illustrates the number of passengers served per road segment regardless of the actual operator used with Uitenhage/Commercial Road having the highest demand of over 50,000 trips per day when scaled up to 100 %. Overall, the average waiting time for boarding a minibus is 4 min 20 s in the model which matches the 5 min estimated by local expert knowledge.

For validation purposes, counts data of minibus passengers is derived from the Transport Plan (SSI Engineers and Environmental Consultants, 2011). As Figure 6 shows, the

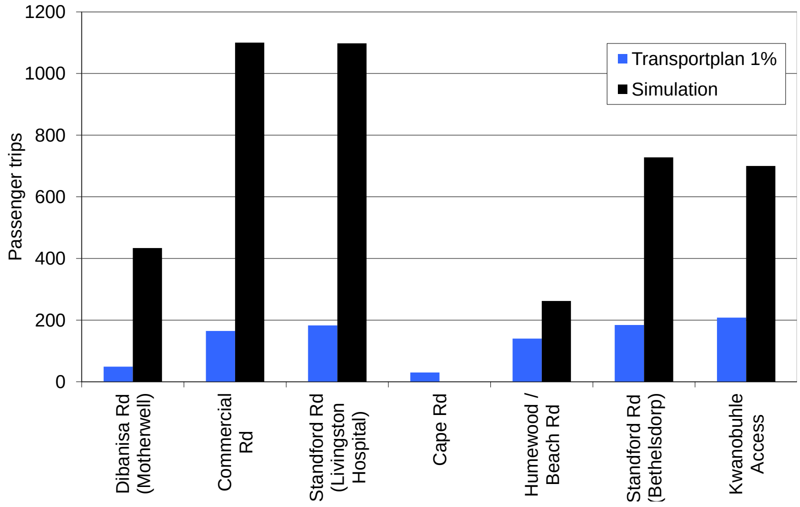


Figure 6: Comparison of minibus passenger counts data

figures of the simulation compared to the provided counts data reveals a large discrepancy in numbers. However, the counts data stated in the Transport Plan derives directly from a simulation with no further explained input data. Since, the demand of our scenario originates from a comprehensive household survey the number of trips and locations stated in the survey and thus in our model are considered more reliable than the figures stated in the Transport Plan.

One might notice that the "Cape Rd"-countstation shows a simulated value of zero whereas the Transport Plan states an albeit low value. Sensitivity tests show that the road segment of that count station is served only occasionally. This is mainly for two reasons. Firstly, the surroundings of the count station feature only a few activities yielding in a low attractiveness of serving this area directly. Secondly and more important, due to the count station's location at the edge of the minibus' service area the probability for a minibus *route* passing by is very low. Furthermore, the dense network in this area provides plenty of opportunities to circumvent the count station itself by making smaller detours.

5.3 Boarding and alighting of passengers

As illustrated in the leg-histograms shown in Figure 2, the population using the minibus system features two demand peaks, one in the morning from 7 to 8 o'clock and one in the afternoon between 14 and 15 o'clock. In addition, the activities of the most common home-work trips of minibus users form spatially separated clusters. In consequence, boarding activities of minibus users going to work in the morning concentrate at different locations than the corresponding alightings. For example, boarding activities during the morning peak as shown in Figure 7a tend to be scattered in residential areas whereas alighting activities (Figure 7b) occur more clustered and in areas with workplaces, see Figure 1 for comparison.

The analysis of the afternoon peak's boarding activities (Figure 7c) features the same hot-spots as the alightings during the morning peak. In addition, there are a few new hot-spots especially in the Township of Motherwell in the north-east of the research area. These trips are related to the (primary) schools situated in that area. Since the scholars tend to live nearby and just walk, the minibus trips belong to the employees of the schools leaving the township when the school day ends.

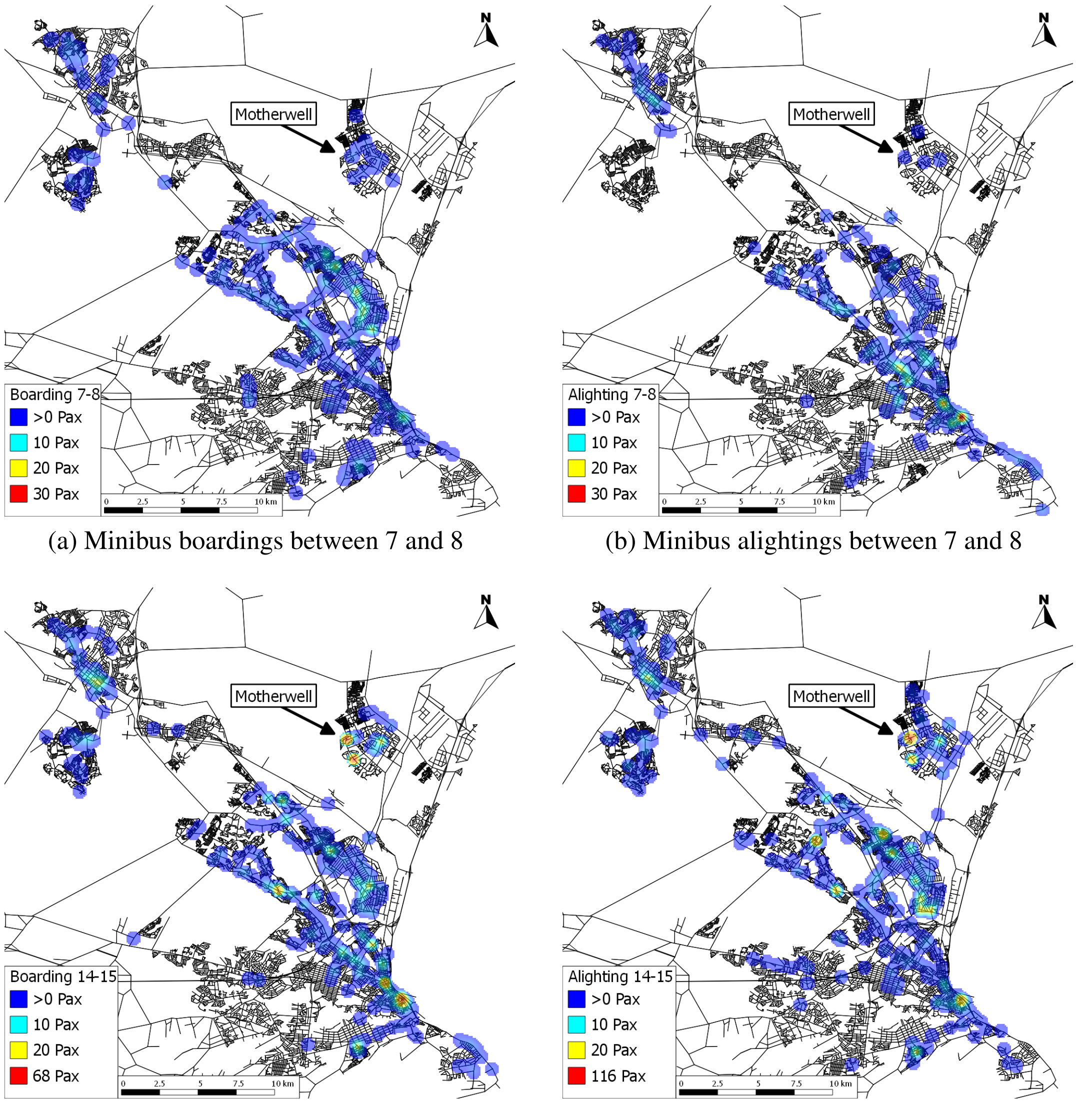
5.4 Discussion

The evolved minibus network analyzed in this section heavily depends on the configuration of the minibus model. Especially the cost structure has a huge impact on the service quality of the minibuses. Given the fare is set to a value experienced by the authors, the average load factor a driver needs to cover its expenses derives directly from its running costs. As stated earlier in section 2, it becomes the goal of the driver to earn the agreed check-in amount for the vehicle owner. Since little is known about these agreements, the authors had to rely on an educated guess on what costs the vehicle owners have to cover and thus, the drivers need to earn.

From transport planning studies conducted for the public transport authority of Berlin, Germany, the sensitivity of the minibus model towards changes of the cost structure is known. Higher fares or smaller running costs directly translate into smaller average load factors. This is a direct result of the vehicle owners always balancing their budget to zero, see subsection 3.4. Thus, the vehicle owners put more vehicles into service when serving the same amount of passengers. As a consequence, high demand corridors are served more frequently and the number of denied boardings due to the capacity constrains of the vehicles decreases. Moreover, the vehicle owners are able to provide more services in low demand areas which could not cover the related costs before. Effectively, this increases the total coverage of the minibus network and reduces access/egress walking distances.

6 Conclusion and Outlook

The *minibus model* presented in this paper, we would claim, is able to create "close-to-reality" *minibus networks* in a South African context. The networks evolve according



(a) Minibus boardings between 7 and 8

(b) Minibus alightings between 7 and 8

(c) Minibus boardings between 14 and 15

(d) Minibus alightings between 14 and 15

Figure 7: Boardings and alightings during the morning peak and the afternoon peak. Boardings and alightings induced by transfers are excluded.

to the constraints of the input data given. In case detailed minibus data on routes and headways is available, the model can also be used to simulate a fixed minibus supply. In both cases the minibus-specific behaviour is integrated into an existing multi-modal transport model. Transport planners and policymakers can thus analyze the implications of policy measures like the currently debated implementation of a minibus (taxi) subsidy.

Being able to realistically mimic the behavior, for the first time, of the taxi stakeholders opens a number of opportunities for decision-makers. This is possible because if the model encapsulates behaviour, testing different scenarios may yield changes in behaviour, be it by the driver (route variation), the owner (vehicle size and mix), or the association (route fares). What are some of the scenarios? When introducing a new formal bus rapid transit (BRT) line, resistance from the taxi industry has seen a few instances where the BRT lines are jointly operated, and owned, by the taxi industry (Joubert, 2013). An ex-ante analysis of what impact the BRT line will have on the taxi industry may support negotiations on the number of taxi vehicles that will be removed from the line with the new high-capacity BRT vehicles.

Another example may be the introduction of road pricing, as is planned elsewhere in the country. The fee and discount structure of the toll, for example a discount for public transport vehicles, or time-of-day discounts, can be evaluated. Testing the fee structures in an agent-based setting can help determine how minibus taxi routes may evolve, how the fare structures change, and ultimately what the financial implications would be for commuters that already represent the low-income quartile. It may also assist in identifying unintended consequences that may, for example, result from newly congested areas created as a results of other road users diverting.

As far as reliable validation data is available the network represents the coverage and main characteristics of the real minibus system of the *Nelson Mandela Bay Municipality*, and reflects the minibus users' travel pattern. However, the model can be further enhanced to incorporate more South African specific travel behavior. This includes ceasing service outside the peak hours and integrating vehicle holding strategies at the minibus routes' termini (taxi ranks) to reflect the drivers' tendency to depart only with nearly fully loaded vehicles. Furthermore, future implementations should depict the fact that usually only one operator serves a certain relation. Another issue derives from the diversification of service types. While local and long distance routes overlap, both services charge different fares and thus, minibus users are more willing to board a local minibus if it serves the same trip with equal or better quality. With the recent implementation of fares into MATSim's router architecture this becomes possible and trips can be calculated with respect to the preferences of individual travelers. After implementing fares into the current model a second step will be the implementation of a detailed decision model – based on intrinsic motivation and personal income – to represent the agents reaction to changes of the system, e.g. to evaluate the influence and acceptance of new public transport systems.

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