Person-Based Dynamic Traffic Assignment for Mixed Traffic Conditions

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Abstract

For developing countries where mixed traffic conditions prevail, it becomes necessary to add the influence of all types of vehicles. The absence of lane discipline makes traffic flow modeling even more complex. Patna, the capital of the state Bihar in India, is one example. In the present study, Patna Municipal Corporation traffic is analyzed using a microscopic dynamic traffic assignment approach. For this purpose, the software package MATSim (Multi-Agent Transport Simulation) is used which employs demand generation using an activity-based model. Advantages of MATSim include tracing travelers and their activities throughout the day and being able to simulate large regional scenarios. However, its traffic flow model, the queue model is not very detailed, so it was unclear if it could deal with heterogeneous traffic.

This paper considers several enhancements to the MATSim queue model, and discusses their capabilities and limitations to simulate mixed traffic. These enhancements reach from the capability to simply add vehicles with different maximum speeds and different sizes into the existing FIFO (First-In-First-Out) queue model to a more realistic modified queue model in which faster vehicles can pass slower vehicles. The enhancements are discussed with their fundamental diagrams for traffic flow and with a view towards travel time distributions by mode in Patna.

Keywords: Dynamic traffic assignment; MATSim; Heterogeneous traffic; Mixed traffic; Passing; Fundamental diagrams for traffic flow; Multiple mode simulation.

1. Introduction

1.1. From the four step process to person-based simulation

Transport planning is a difficult problem, since many elements of the system interact in complex and often unpredictable ways. For this reason, computational models are used to inform the decision-making process. The traditional model is the four step process (McNally, 2007). Both from a theoretical and from a practical perspective, the four step process, at least in its traditional incarnation, is insufficient, at least for the following two reasons:

- The four step process does not allow any kind of (within-day and day-to-day) dynamical development in the system.
- The four step process does not allow any kind of dis-aggregated, "behavior-oriented" decision-making.

The second item does, in fact, depend on the first: without a coherent representation of time-of-day it is difficult to represent issues such as schedule delay, unreliability, being consistently late in an activity chain because of a traffic delay in the morning, spontaneous adjustments, etc.

Two streams of research have developed in order to overcome these difficulties. **Dynamic Traffic Assignment (DTA)** (Peeta and Ziliaskopoulos, 2001; Carey and Watling, 2003) assigns traffic dynamically over the day, typically with so-called physical queues that grow and shrink. **Activity-Based Demand Generation (ABDG)** generates

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person-centric activity chains over the day for every member of a synthetic population that represents the real population of a city or region.

DTA and ABDG are conventionally coupled by passing time-dependent, e.g. hourly, origin destination matrices from the ABDG to the DTA. It has been argued (Balmer et al., 2004) that this type of coupling fails to exploit the full potential of behavioral dis-aggregated modeling, and that rather the synthetic person should be the unit that is passed from the ABDG to the DTA (or more general: "to the network loading model"). In recent time, there has been a tendency to pass individual trips (i.e. trip starting time, trip origin and destination) instead of aggregated matrices (DynusT www page, 2012). Few projects have moved to a fully person-centric approach, one of them being our own MATSim project (e.g. Balmer et al. (2009), also see Miller et al. (2004)).

1.2. Mixed traffic

In this paper, it will be argued that the person-centric method is also very useful for a consistent approach when considering mixed traffic conditions at the regional scale. The problem is especially severe in developing countries where mixed traffic conditions persist. Traffic in India comprises of a variety of vehicles; these vehicles have different static (dimensions of vehicles) and dynamic (speed and acceleration of vehicles) characteristics. There is no restriction on the movement of such vehicles and hence the concept of lanes is rare. Since no physical segregation is provided for different vehicle types, vehicular interaction between all vehicle types is also abundant. Cars, buses and other vehicles share the same road space. Other vehicles include bicycles, three-wheeler motorized vehicles, and non-motorized rickshaws. Despite a low share of cars, mixed traffic conditions cause congestion and higher chances of conflicts.

Homogeneous traffic flow models are unable to help in engineering the infrastructure that provides better mobility and safe movement in heterogeneous conditions (Tiwari, 2000). Dey et al. (2008) did simulation for mixed traffic on two lane roads. The paper illustrates the effect of traffic mix on capacity, speed etc. Two roadways having similar physical attributes will have different flow characteristics under homogeneous or non-homogeneous traffic, and also under the presence or absence of lane concepts.

Hence, this paper aims to study such roadway conditions, flow characteristics and travel behavior in mixed traffic situations with modifications of the traditional queue model, and the consequences to a regional DTA investigation. Sec. 2 describes the MATSim framework, Sec. 3 demonstrates the data used for the study, Sec. 4 explains the modeling from the data, Sec. 5 introduces the modifications to the queue model and analyzes some of their properties with fundamental diagrams for traffic flow and space time trajectories, Sec. 6 and 7 shows the results of the study for 'without mode choice' and 'mode choice' cases and in the end the study is concluded.

2. MATSim

The MATSim framework can be divided into two layers (Nagel and Marchal, 2007; Raney, 2005):

- The first layer is known as the *physical layer* which represents all physical aspects of the environment. It contains the physical dimensions of the road infrastructure, as well as information about the activities performed by the persons in the physical world. The simulation of the persons in a synthetic version of the physical world is sometimes called *mobility simulation*. For each simulated individual, the mobility simulation simultaneously executes a mobility plan in the synthetic physical environment.
- The second layer is the *strategic* or *mental layer* which computes the strategies for individuals. All travelers have some daily routine plan which they want to follow. It includes schedules of all activities, locations, travel modes, as well as behavioral parameters which enable people to change their plan in reaction to feedback from the physical layer.

The mobility simulation implemented in MATSim is based on a time step based queuing model (Gawron, 1998; Simon et al., 1999). To start the simulation, one needs a physical boundary condition (the road network) which will remain unchanged throughout, and an initial condition (demographic household data and a sequence of localized activities per synthetic person). A typical MATSim framework consists of repeated iterations of the following three steps:

1. **Execution:** A simulation of all the individuals with their selected plans takes place simultaneously in the physical environment. This is done by the traffic mobility simulation.

2. **Scoring:** A score for the selected plan of every simulated individual is determined. Various scoring functions can be used; standard MATSim uses the Charypar-Nagel scoring function (Charypar and Nagel, 2005).
3. **Re-planning:** Re-planning takes place depending on strategies and their probabilities. Strategies come in two flavors:

   Choice set modification: innovative strategies and plans removal So-called innovative strategies select an existing plan, make a copy of it, and modify the copy. Examples for innovative strategies are modifications of the routes, the times, the modes, the activity locations, etc. This modified copy is then made selected, and thus executed in the next iteration. If, at the end of that iteration, the agent has more plans than a configurable number, the worst plan is removed.

   Choice: plan selection strategy Agents not selected for choice set modification select between existing plans according to a model which generates a logit distribution.

   A weight is assigned to every strategy, probabilities are computed based on these weights and re-planning takes place depending on the probabilities: If two strategies are assigned equal weights, then each person has an equal probability of using one or the other. In this paper, initially only route choice and time choice are used; later in Sec. 7 mode choice is also used.

3. Patna Data

Patna, a medium sized city in eastern India, has very poor traffic conditions. The total available road network in Patna is around 5% of the total development area, and thus the city is struggling with congestion problems especially during the peak hours (Singh, 2004). For this study, the area of the Patna Municipal Corporation (PMC) is considered, and is simply named as "Patna" from now on.

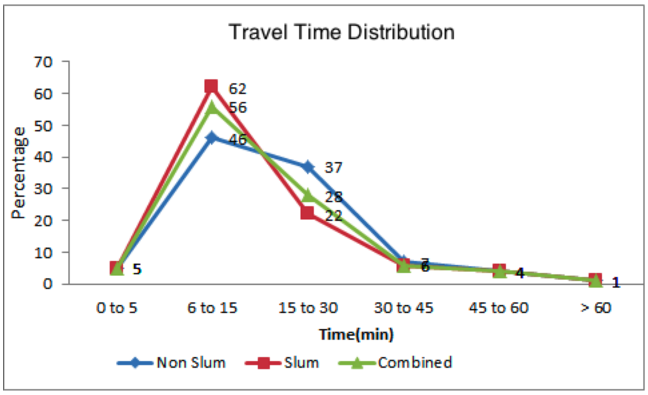
Household data. The population of the Patna agglomeration area was 5.77 million in 2011 (Census, 2011). The study area includes 72 zones of the PMC with a population of 1.57 million for the year 2008. The development of Patna is linear, and along the river Ganga, from east to west. The land use pattern is unplanned and mostly residential. Commercial activities are distributed along arterials and sub-arterials. Most of the industrial activities are in the "old city". The data available is based on a comprehensive transportation planning study conducted on Patna, capital of Bihar (from now on called "Patna Comprehensive Mobility Plan" (Patna CMP); iTrans, 2009). The whole population is divided into two groups based on income level, so-called "slum population" and "non-slum population". Households below poverty line (BPL) are called "slum households". These households do not have even basic amenities; because of their income level they are not able to fulfill their elementary socio-economic needs (IPE, 2006). Most of the slums are concentrated along river Ganga, near the railway station, and in the eastern part of Patna.

Network data. The road network (Fig. 1a) of Patna is divided into 3 major road categories namely major arterial, arterial and collector street. It has three major corridors, called Ashok Rajpath, Old bypass and New bypass, which are spread along the length of the city. 36% of total road length have a width less than 5 m, with an accordingly low capacity. These roads are mostly in the eastern part of Patna. Any location inside Patna is at most one kilometer away from an arterial or a sub-arterial.

Count data. The Patna CMP also provides traffic count data for 6 stations as shown in Fig. 1a. Vehicles are counted hourly between 6 am and 10 pm. These counts are categorized based on the type of vehicles (cars, motorcycles, bicycles etc.). This data is used to validate the model.

Trip characteristics. Patna has mixed traffic (see Table 1). In particular, it can be observed that bicycle trips form a significant portion of the total trips. Fig. 1b shows the distribution of travel times for different population groups. More than 85% of people have a travel time less than 30 minutes.

(a) Road network of Patna and 6 count stations



(b) Travel time distribution from Patna CMP

Figure 1: Road network and travel time distribution for Patna. Source: after iTrans (2009)

Table 1: Average trip length, average travel time, mode share. Source : iTrans (2009)

mode	average travel time (*min*)	average trip length (*km*)	share
Bus	Data Not Available	Data Not Available	5%
Mini bus	20.45	5.80	4%
Car	21.43	7.15	2%
Motorized two-wheeler (motorcycle)	18.56	5.91	14%
Motorized three-wheeler	23.78	7.15	9%
Bicycle	19.94	4.98	33%
Walk	19.28	1.59	29%
Cycle-rickshaw	25.33	5.11	4%

4. Modelling

Patna network. To create a digital MATSim network for the Patna scenario, TransCad (TransCAD, 2011) files are used as input files. These files are a part of the data provided by iTrans (2009).[1] The hourly capacity is then computed

[1] A few disconnected links in the network file received from iTrans are joined. This concerns some major arterials, and was checked with Google Earth. The reasons for the disconnected links are unknown.

according to Chandra and Kumar (2003) as

$$Capacity = -2184 - 22.6 \times w^2 + 857.4 \times w \tag{1}$$

where w is the width of the road in meters. A minimum capacity of 300 PCU/hr per direction is used, where 'PCU' refers to 'Passenger Car Units'. The resulting network has 3505 nodes and 7542 links.

Demand generation. Travel demand for Patna is generated directly from a trip diary survey provided by iTrans (2009). Parts of the data in the household survey were unavailable; for such cases the required data was imputed based on other available data. Home based work trips were thus synthetically generated from available trip plans.

This results in 13,122 activity records, 10,111 of them are non-slum and 3,011 are slum. Every such record is translated into one MATSim person with one MATSim plan. Compared to 1.24 million trips (trip production is 79%) for the 2008 population of Patna (iTrans, 2009), this represents approximately a 1% sample of all trips. As long as schedule-based transit assignment is not used, decent results with MATSim can already be obtained from 1% population samples (Nagel, 2008, 2011).

Configuration parameters. In addition to a network, plans and counts, the simulation postulates several configuration parameters. The iterations were essentially run as standard Dynamic Traffic Assignment iterations: in every iteration, about 10% of travelers were given a new route that would have been fastest in the previous iteration. An additional approximately 5% of travelers are given new plan where all their activity end times were shifted randomly between -2 and $+2\,hours$ ("time mutation"). The simulations were run for 200 iterations; re-planning was switched off after 160 iterations. Travelers switch between plans with an algorithm that converges to a logit distribution, i.e. the probability to select a plan i with score S_i is $e^{S_i} / \sum_j e^{S_j}$.

The parameters used to calculate the score are

- The synthetic persons are assumed to accumulate utility when they **perform an activity**. The underlying function is logarithmic; its linearized version at the operating point can be approximated with a marginal utility of $6\,utils/hr$ (called `performing` in the MATSim configuration).
- If these synthetic persons are **traveling**, they does not incur any marginal (dis-)utility directly, but they are implicitly penalized by opportunity cost of time i.e. by $-6\,utils/hr$. It is assumed to be the same for all modes here (`travelingCar, travelingBike, ...`).

In addition, the traffic flow behavior is scaled down to the population sample size as follows:

- The **flow capacity** factor (`flowCapacityFactor`) is used to scale down the link capacity depending on the ratio of number of persons (13122 plans) in the simulation and total trip production (1.24 million trips; see Sec. 4). It is therefore set to 0.011.
- The **storage capacity** factor (`storageCapacityFactor`) is taken as three times of flow capacity factor (i.e. 0.033) to avoid any artifacts on the links with shorter length or smaller flow capacity.

5. Mixed traffic modelling

5.1. Congested modes

Congested assignment (e.g. Ortuzar and Willumsen, 2002; Sheffi, 1985) assumes that route choice, via the network loading, leads to congestion, which in turn affects route choice. In this context, it is important to consider which mode(s) actually cause congestion. Until the present study was done, MATSim was designed for car traffic as congested mode. However, from Sec. 3 it is clear that this would not work for Patna since both motorcycle and bicycle are more important modes than car, and they cause congestion as well. MATSim was in fact previously applied to another congested mode, namely pedestrian, by re-scaling speed, flow capacity, and storage capacity (Lämmel et al., 2008). Yet, these are link parameters, which means that the approach only works as long as the moving items are all the same. For this study, we extended the mobility simulation with the option of associating the congested mode with a *vehicle type*, which has maximum speed and passenger car units as attributes. This lays the foundation for having multiple congested modes, which is discussed in Sec. 5.6. The calculation of passenger car units is discussed in Sec. 5.3. The maximum (network) speeds of car, motorcycle and bicycle are set to 60, 60 and 15 km/h respectively.

5.2. *Uncongested modes*

All other modes, which are not simulated on the network, are *teleported*. This means that every time the traffic flow simulation encounters a leg with a mode that is not registered as "congested" mode, it will note a departure, compute the expected arrival time according to the beeline distance of the leg divided by the mode-specific teleportation speed, and set a timer. When the arrival is due, the traffic flow simulation will note an arrival and the person will start its next activity. It means that trips with modes that are not physically executed in the traffic flow simulation are still logically executed, with the difference that there is no information about the chosen route through the network, and these trips are not influenced by other events in the system and events in turn are not influenced by them. A big advantage of this is that, in this way, a simulation can be started with an arbitrary set of modes, and most types of analysis (e.g. trip distance distribution by mode, travel time distribution by mode) are still possible. Clearly, they are approximated, but also a congested network loading model is an approximation, albeit a better one.

There is, in principle, a concept called *beeline factor* in MATSim that designates how much detour an actual trip takes compared to the teleported distance. This factor, however, is the same for all modes, which is not considered realistic for Patna where pedestrians can go much more directly than, say, cars. In consequence, the beeline factor is set to 1.0 for all modes, and the issue is dealt with via the mode-specific teleportation speeds and post-processing. The (beeline) teleportation speeds are assumed as 4 km/h for walk, 10 km/h for bicycle and 20 km/h for public transport, car and motorcycle. The distance traveled by these modes as reported by the simulation will now be the beeline distance. Therefore, to calculate the effective distance for those modes, effective beeline distance factors are introduced in the post-processing. These factors are assumed as 1.1 for walk, 1.2 for bicycle (if teleported), 1.5 for public transport and, 2.0 for car and motorcycle (if teleported).

An improved variant for the uncongested modes is provided by Dobler and Lämmel (2012) (implemented as the "multiModal" option in MATSim). Here, uncongested modes are not teleported, but moved along a network. There is, however, no congestion on the links, but vehicles leave links at their free flow link exit times. Compared to teleportation, this has the advantage that a sequence of links will be noted by the simulation, which may be beneficial for some analyses, and is the minimal requirement for meaningful en-route re-planning in these modes. That approach was not used for the present study, since it is unrealistic to assume that pedestrians would only use the planning network that was available.

5.3. *PCU calculation*

There are several methods available to get passenger car units for different vehicle entities, for example:

- IRC-106 (1990) provides PCU factors for motorcycle as 0.5 and 0.75 for having 5% and 10% (and more) motorcycles in the traffic stream. Similarly, for bicycle these values are 0.4 and 0.5 for 5% and 10% (and more) bicycles in the traffic stream.

- According to Mallikarjuna and Rao (2006), the PCU factor for any vehicle depends on the area occupancy measured over space and time; they used a cellular automata approach. A range of PCU factors for each vehicle entity is given depending on its area occupancy.

- Tiwari et al. (2007) calculate the PCU factor for heterogeneous traffic using a modified density approach. They provide PCU factors as 0.51 and 0.44 for motorized two-wheelers and non-motorized two-wheelers.

The factors stated above are not used in this study since all factors are influenced by the density and are based on a static approach, i.e. an approach that averages over all speeds. Speed, however, is treated separately in MATSim for all vehicles, therefore the use of these factors would overestimate the PCU value for all vehicles. The approach in the present investigation is similar to Mallikarjuna and Rao (2006, 2011), but without its speed dependency. The effective area occupied by vehicle j is calculated, and the ratio of area occupied by vehicle j to area occupied by a passenger car is taken as PCU factor for vehicle j. Other factors affecting PCU are assumed to be same for all vehicles. The dimensions of the vehicle entities and lateral clearance are assumed as mentioned in Table 2. Table 2 shows the PCU calculation for the study scenario. All other factors are assumed to be the same for all vehicles.

Table 2: PCU calculation

Vehicle type	Length	Width	effective width	Area	PCU calc	PCU taken
Car	4.1	1.6	2.6	10.66	1	1
Motorcycle	1.8	0.6	1.4	2.52	0.2364	0.25
Bicycle	1.8	0.5	1.3	2.34	0.2195	0.25

5.4. Fundamental Diagrams (FDs)

Traffic flow theory has three fundamental variables, namely flow, density and speed. The primary relationship between the three is $q = \rho v$ where q is the traffic flow, ρ is density and v is the speed. In the last decade, several authors have attempted to extend traffic flow theory for mixed traffic. Wong and Wong (2002) extended the LWR model to develop a multi-class traffic flow model. The authors grouped heterogeneous drivers based on their speeds. Using the model, the authors replicated reverse-lambda shape of flow density curve. In the end, the authors concluded that the discontinuity in fundamental diagrams is not a result of the operational (mixed traffic) regime but a result of user interactions. Li et al. (2010) derive the phase diagrams for mixed traffic with help of flow density plots depending on varying fraction of faster and slower traffic mix on the cross road. Hong-Wei et al. (2011) investigate dynamics of the motorized vehicle with non-motorized vehicle by considering lateral friction and overlapped driving. Vasic and Ruskin (2012) present a new approach to modeling mixed traffic including bicycles by introducing different sized cells in cellular automata approach. The authors examined the car-bicycle interaction using two scenarios 1) at a road section and 2) at left turn and then showed fundamental diagrams for car as a function of bicycle density for both scenarios.

We use FDs to study how the queue model of traffic flow behaves with respect to different vehicle types with different sizes and maximum speeds. Since this model is then used to simulate mixed traffic conditions in Patna, it is important to first analyze basic properties of the model under simple conditions.

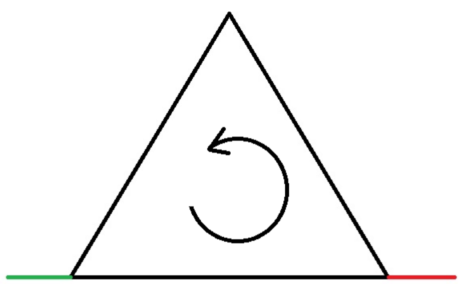


Figure 2: Simple network used for generating the fundamental diagrams

To generate FDs, a test scenario is considered with a simple network in the form of a race track as shown in Fig. 2. The race track has 3 links of length 1000 m each. Vehicles enter the track on the left-hand side and then drive in circles while the observable simulation properties average speed, flow and density are measured. When these quantities have stabilized, the simulation is terminated. The number of simulated vehicles is varied, resulting in data points for varying densities. The maximum number of vehicles on the network is limited by its storage capacity, a property of the queue model, where a vehicle of 1 PCU uses up, by default, 7.5m of space. This results in a cut-off at around 150 PCU/km. Higher densities are unreachable, and we do not attempt simulation runs with more vehicles. The maximum flow is also a simulation parameter. In this experiment, it is set to 2700 PCU/hr. Vehicles of three different types, namely car, motorcycle and bicycle, are put on the network in different combinations. Motorcycles have the same speed as cars but are smaller (0.25 PCU), and bicycles are the same size as motorcycles, but slow.

We consider three cases and discuss the resulting FD plots: these are "homogeneous traffic", "mixed traffic where passing is not allowed", "mixed traffic where some version of passing is allowed".

5.5. *Homogeneous vehicle fleets*

Figs. 3a and 3b show the flow behavior for the three cases with only one vehicle type each. Cars and motorcycles on the network differ only in their PCU factors. Densities and flows are measured in PCUs, so the plots for cars (Fig. 3a) and motorcycles (not shown) look almost identical and as expected. FDs have a laminar regime, a capacity regime and a jammed regime as explained in Simon et al. (1999). In the laminar regime, flow increases with density and speed is constant at free speed. In the capacity regime, flow is constant and speed decreases parabolically with increasing density. In the jammed regime, flow and speed decrease with increasing density, finally reaching zero.

It is a peculiarity of the queue model that the jammed regime is unrealistically narrow; this corresponds to the absence of the backwards traveling kinematic wave. (Or more technically: The backwards traveling kinematic wave travels with the speed of one link per simulation time step.) It is well known that this is a shortcoming of the queue model (Simon et al., 1999), yet our consistent practical experience is that for large-scale applications this is an acceptable trade-off in order to obtain high computational speeds.

Fig. 3b is for bicycles only. In this case, flow grows linearly with density, up to a value smaller than the maximum flow capacity of the link, and then abruptly drops. The reason is as follows: Free speed determines the rate of the linear increase in flow in the laminar regime. For a lower free speed, the point of maximum flow is reached only at a higher density. In the case of bicycles, free speed is so slow that the maximum flow is not reached before the maximum density, so that the capacity regime does not exist and the laminar regime changes directly into the jammed regime.[2]

5.6. *Mixed traffic without passing*

In Sec. 5.1 it was pointed out how the single congested (network-simulated) mode could be chosen. It is, however, plausible to assume that for Patna having only one of the modes as congested will not be sufficient, thus interactions between modes need to be included.

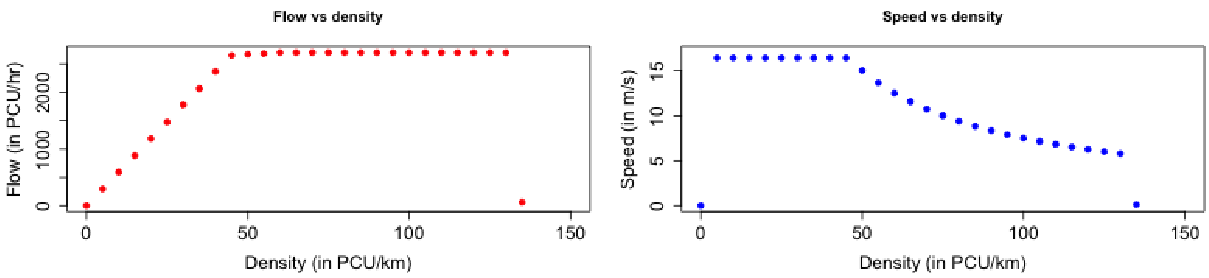
The first approach investigated in this study is using the queue model to simulate several modes together on the same network. In this case, the simulation observes each vehicle's free speed link travel time, and flow and storage capacity constraints are observed using each vehicle's PCU. Since for this version, the queue model is not changed and in its original form, it does not account for vehicles passing each other, the vehicles remain in First-In-First-Out (FIFO) order.

In order to explore the flow characteristics in such scenarios, vehicle types having substantial difference in their speeds are simulated on the test track. Fig. 3c shows FDs when car, motorcycle and bicycle are simulated. Equal (by PCU) modal split is used (1 car : 4 motorcycles : 4 bicycles). Plots are identical for all vehicle types because passing is not allowed and thus cars and motorcycles are following bicycles. Where slow vehicles are involved, the capacity regime does not exist (see Sec. 5.4), so all vehicles have similar FDs. Similarly FDs for mixed traffic consisting of car and bicycle are also plotted (not shown in this paper) with equal modal split. These plots also look same as long as there is a single slow vehicle which governs the speed of other vehicles. When mixing vehicles of equal maximum speed, such as cars and motorcycles, one obtains approximately the same plot as Fig. 3a, except that the flows are divided by two since the respective share of that vehicle type is divided by two. Overall, it can be concluded that, predictably, flows and speeds of faster vehicles are governed by the speed of the slower vehicle when passing is not allowed in the model.

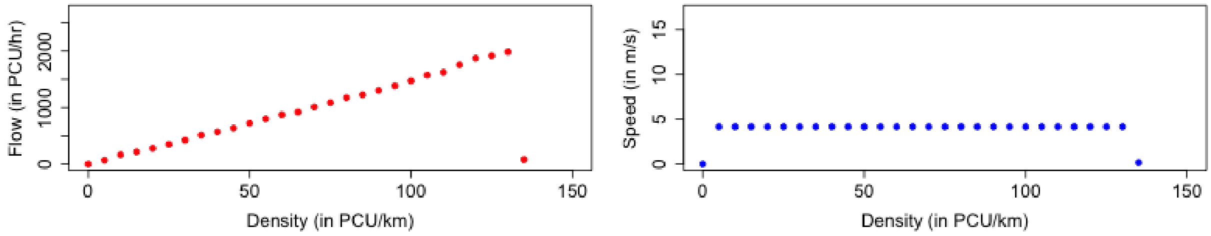
5.7. *Mixed traffic with passing*

As a reaction to the previous version, a very simple replacement was implemented. For this, the ordering of the vehicles for the link exit was no longer in the sequence in which they entered the link, but in the sequence of their *earliest link exit time*, which is the time by which the vehicle would reach the end of the link if it was only constrained

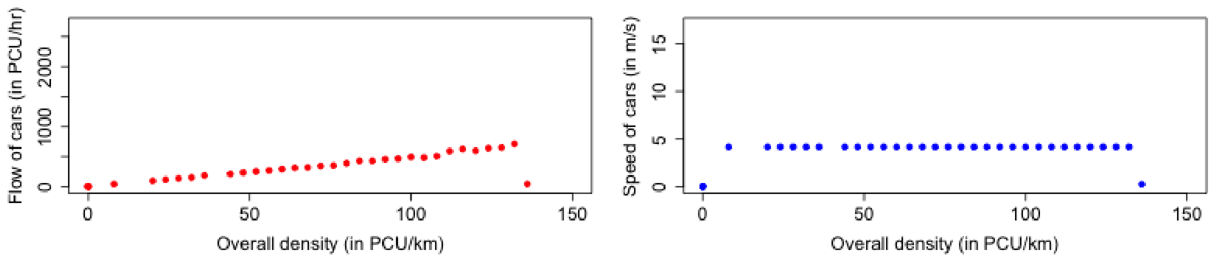
[2] There is actually a provision inside MATSim to ensure that the maximum flow of a link is always reached with vehicles that reach the free speed of the link. Clearly, that provision is no longer active once vehicle are slowed down below the link free speed by a lower vehicle maximum speed.



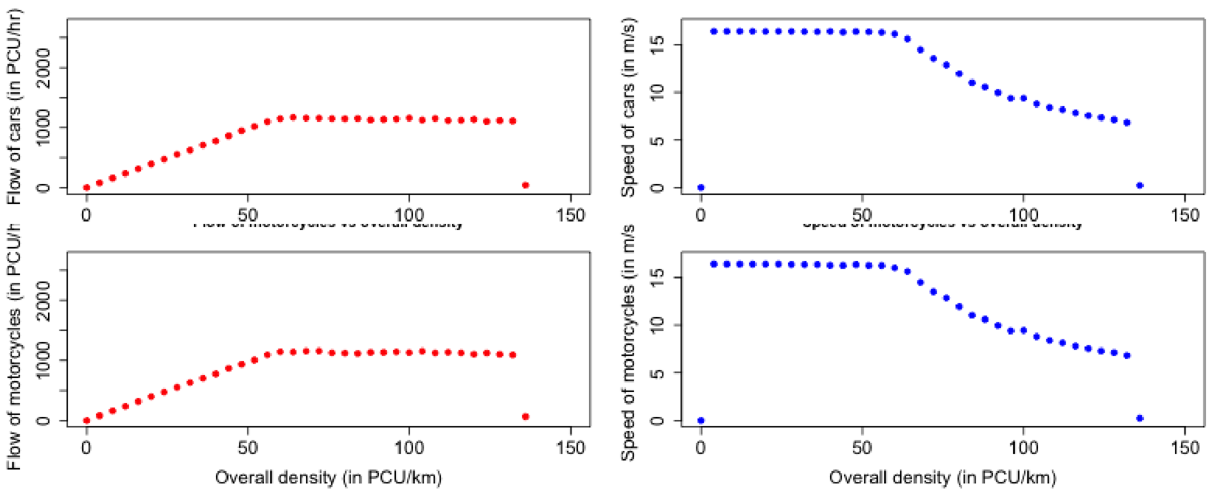
(a) FDs for simulation runs where only cars are on the network. Repeating this for motocycles gives identical results.



(b) FDs for simulation runs where only bicycles are on the network.



(c) FDs for mixed traffic consisting of equal PCU shares of cars, motorcycles and bicycles. Passing is not allowed. All vehicle types have identical plots: the slowest vehicle type (bicycles, shown here) dictates the dynamics.



(d) FDs for mixed traffic consisting of equal PCU shares of cars, motorcycles and bicycles. Passing is allowed. Plots for motorcycle (not shown) are identical to plots for car.

Figure 3: Fundamental diagrams (FDs) for experiments on the simulated test track

by the maximum speed of the vehicle type and the link as shown in Fig. 4. Flow and storage capacity constraints are still observed, and the vehicle type specific PCU are taken into account. It means that a sufficiently fast vehicle can pass other vehicles whose earliest link exit times have not yet been reached. These are the vehicles which are on the link because, even at their maximum free speed, they could not have reached its end yet. It does not include those vehicles which are on the link because they are kept there by a capacity constraint, i.e. whose earliest link exit time has already passed. This behavior should be approximately correct in the uncongested regime: here, both vehicle types just pass each other freely. In the congested regime this model predicts that passing is possible during the free speed travel time, but impossible afterwards. In many situations, the former will be wrong, because passing may not be possible anywhere on a congested link. Conversely, it may happen in reality that bicycles are actually *faster* than cars in the congested regime; this is also not picked up by the model. Still, the model has the advantage that it keeps the fast computational performance of the queue model where vehicles are only considered when they enter and leave the link and never in between (Zilske et al., 2012).

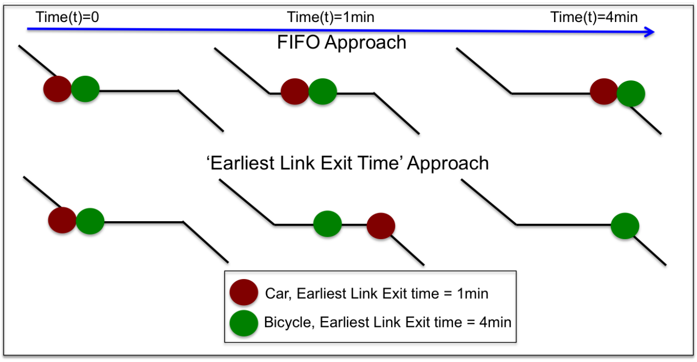


Figure 4: FIFO Approach and Passing of bicycle by car on a link (not to scale)

Fig. 3d is obtained with cars, motorcycles and bicycles together, again with equal modal split in PCU terms (1 car : 4 motorcycles : 4 bicycles). The speeds of cars, motorcycles and bicycles are almost the same as the respective free flow speeds till density reaches 60 PCU/km. At this point, the flow reaches about 1150 PCU/hr, 1150 PCU/hr and 300 PCU/hr for cars, motorcycles and bicycles respectively. The reason for different flows at this point is the difference in the speed of vehicles; faster vehicles (cars and motorcycles) are allowed to pass slower vehicles (bicycles). In the same figure, the flow of bicycles increases till the start of capacity regime – i.e. flow of 400 PCU/hr –, then it keeps increasing but at a slower rate till the start of the jammed regime, and finally in the jammed regime it starts decreasing. This is different from Fig. 3b, where the flow of bicycles increases at a constant rate till the start of the jammed regime.

FDs for the mixed traffic consisting of cars and bicycles, when passing is allowed, look similar to the bicycle FDs in Fig. 3d. The reason is that in both cases at least one vehicle type has a slower speed than the others.

Similarly FDs for the mixed traffic consisting of cars and motorcycles, when passing is allowed, look very much like with the case for mixed traffic consisting cars and motorcycles, when passing is not allowed (not shown). This is because of the same speed for both vehicles. Passing is allowed, but because of the identical free speed, this will make no difference. When converted into PCU, traffic flow behavior of these two components is identical, as is to be expected.

5.8. Space Time Trajectories

Since the queue model has defined positions for vehicles only when they enter or leave links, intermediate vehicle positions $x(t)$ are not available. Such positions can only be reconstructed by making certain assumptions. When making these assumptions, it should be kept in mind that those assumptions are made for the purpose of visualization; the true dynamics is entirely given by the abstract model.

These visual trajectories (cf. Fig. 5) are constructed according to the following principles:

1. When a vehicle enters a link, it will move according to its free speed until it reaches the end of the queue.

2. The queue is composed of all vehicles whose "earliest link exit time" is in the past, *plus* all vehicles who would have moved beyond the upstream end of the queue according to item 1.

See the appendix for details. A consequence of this approach is that vehicles do not join the queue in the same sequence in which they leave the link: For example, a bicycle which leaves a link after a car might still be ahead of it when it joins the queue.

Fig. 5 shows a resulting space-time plot. Cars (in black) and bicycles (in red) enter from the left with constant rate. The plot shows the first link, and a part of the second. After finishing one cycle along race track, i.e. all three links, cars and bicycles re-appear at position 0, together with more new vehicles. Once those two types of vehicles together have reached the end of the link (around time step 280), a queue starts, noticeable by a change of velocities both of cars and of bicycles, growing against the direction of the traffic. The queue starts at the downstream rather than at the upstream end of the link because the model places the flow capacity constraint at the downstream end of the link (cf. Charypar et al., 2007, who discuss an additional upstream capacity constraint).

Note that car trajectories are still faster than bicycle trajectories even "inside" the queue; this is due to the effect explained earlier that they do not join the queue in the same sequence in which they leave the link. This is presumably a bit unrealistic; one would rather assume that bicycles are able to be faster than cars in heavily congested situations. Again, we consider this an acceptable compromise in order to keep the fast computing speed of the network loading model, justifiable in particular in conjunction with the speed-density fundamental diagram for the bicycles, Fig. 3d, showing that bicycle speed is nearly unaffected by the overall density until very high densities.

5.9. Bicycle passing rates

Fig. 6 compares the number of bicycles passed by cars on one link for different modal splits while passing is allowed. For the equal modal split case (in green), the number of bicycles passed by cars is highest. Initially, the number of bicycles passed increases with density; after reaching a plateau with a maximum number of passed bicycles, the number start decreasing to zero in congested regime. Triangles (in violet) show the number of bicycles passed while passing is not allowed; which is zero at all densities as expected. In reality, in congested regime, bicycles seep through the cars and come to front of queue. Oketch (2003) discuss such a 'seepage action' and compare the effect of seepage on saturation capacity at mid block and bottlenecks. Therefore, the plot between density and bicycles passed by faster vehicles will look like as shown by yellow line in Fig. 6, where the negative number of passed bicycles is depicting the reverse – i.e. number of cars passed by bicycles – in higher density region. Further study would required to develop a model that includes realistic behavior of car-bicycle interaction in congested regime i.e. 'seepage action', preferably without losing the computation advantage of the present model.

6. Patna results

The different ways of interaction between the modes described in the previous section were tested using the Patna scenario. Following results are obtained using plans generated from trip diaries (cf. Sec. 4) and mode choice is disabled.

6.1. Congested mode: car

First, the simulation was run with its default configuration. In this configuration, only cars are simulated as congested mode, all other modes of transport are teleported.

The share of cars is 2% only, therefore it is very unlikely that it causes major congestion. This is indeed confirmed. Neither average scores nor average travel distances change much over the iterations (not shown). Also the departure and arrival time distribution (not shown) show no indication of congestion.

Fig. 7a shows the travel time distribution for this case. All car trips have travel times less than or equal to 30 minutes, which is unrealistically fast: the average travel time for cars from the primary survey is more than 20 mins, and the household data is showing that there are some car trips having travel times of more than 30 mins.

All other modes besides car are teleported, i.e. congestion has no influence. The travel time distributions of motorcycle and bicycle are presented anyways to simplify comparability between figures.

Since public transport and walk are always teleported in this study, they will always look the same in the present study. Their travel time distributions are therefore not shown.

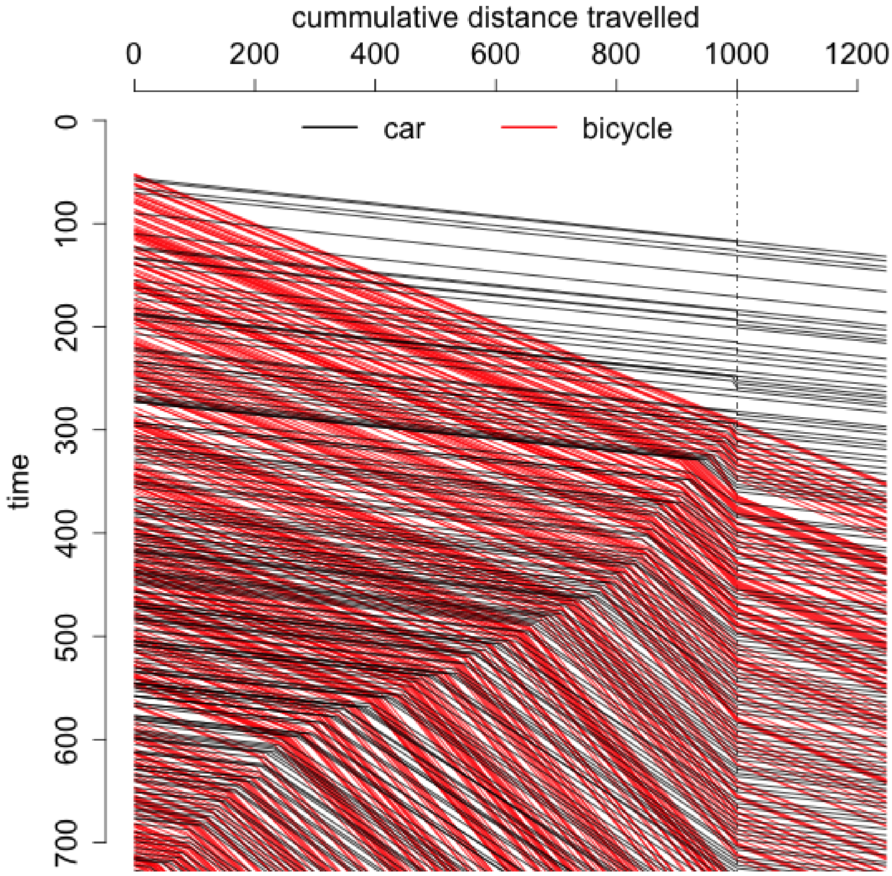


Figure 5: Space time trajectories for car (black) and bicycle (red). Passing is allowed. There is more demand coming in from the left than can be processed according to capacity at x = 1000. In consequence, around t = 280, a queue forms at x = 1000, and its upstream front travels backwards. Both bicycles and cars are affected by the queue, and both in the free speed regime (upstream of the front) and in the queue (downstream of the front), cars are still faster than bicycles. See text for more discussion.

Fig. 8a shows the comparison of average weekday real count vs. average weekday simulation count for iteration 200. Each dot represents one count station in one direction, the middle line is presenting the equal count line. Clearly, the simulation measures fewer vehicles at the counting stations than reality. Possible reasons include:

- External trips are not included in this study because sufficient data was not available. These external trips have significant ratio of cars as they are coming from outside of Patna.
- Since there is little congestion, cars will take the shortest route, thus they traverse fewer links than when the situation is congested.

6.2. Congested mode: bicycle

The share of bicycles for the whole population is 33%, and hence this by itself could cause congestion.

Fig. 7b shows the travel time distribution for different travel modes, in which only bicycle is congested mode and all other modes are teleported. This chart shows that about 85% of bicycle trips have a travel time less than or equal to 45 minutes.

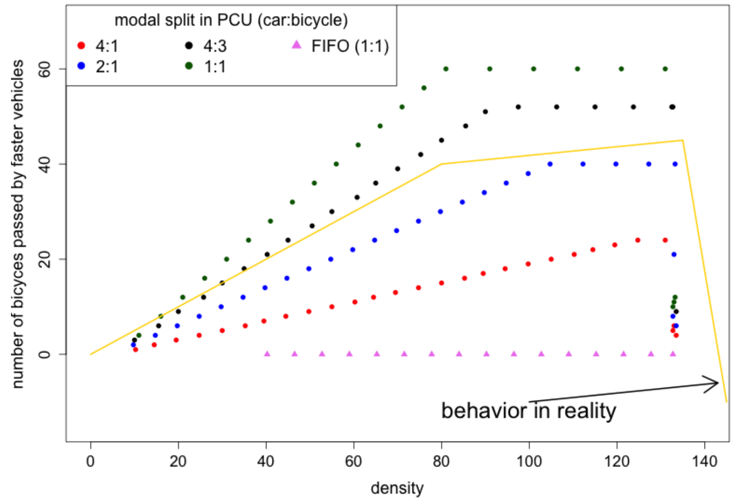


Figure 6: Density vs number of bicycles passed by faster vehicles. Comparison of various modal split and, passing allowed vs passing not allowed.

6.3. Congested modes: car and motorcycle

Combined share of cars and motorcycles is 16%, therefore it becomes important to check for the main mode as cars and motorcycles as well. In Indian traffic conditions, motorcycles pass through congested regime and come in front of queue. MATSim does not allow this functionality therefore it is assumed that car and motorcycle users follow lane discipline, therefore, every motorcycle will stop at the end of queue; it will leave queue based on its link arrival time. Hence, the simulation is also a test of the model that allows multiple congested modes while maintaining FIFO (Sec. 5.6).

The leg histograms (not shown) show that all vehicles reach home again before midnight. However, a significant number of vehicles remains in the system until after 9 pm, indicating congestion.

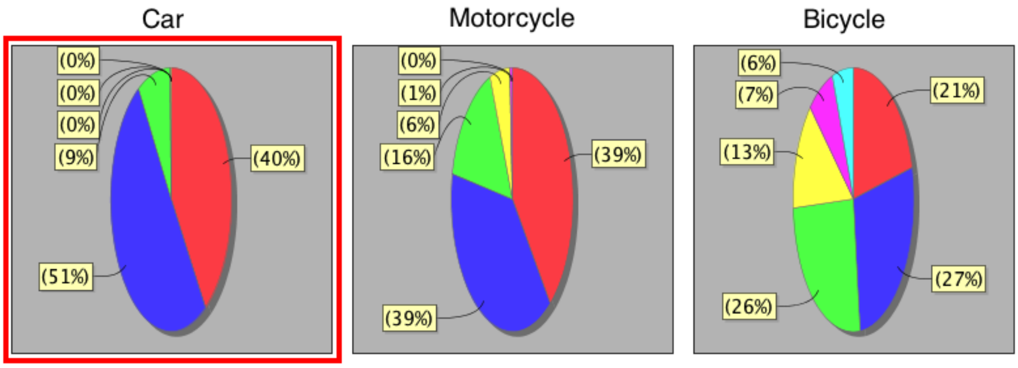
Fig. 7c represents the travel time distribution for all modes. More than 90% of the trips of car users and motorcycle users have a travel time less than 45 minutes. The average simulated travel time for cars and motorcycles is almost same i.e. 15 minutes, while Table 1 shows average survey travel times for cars and motorcycles of 21 and 18 minutes respectively.

6.4. Congested modes: car, motorcycle and bicycle

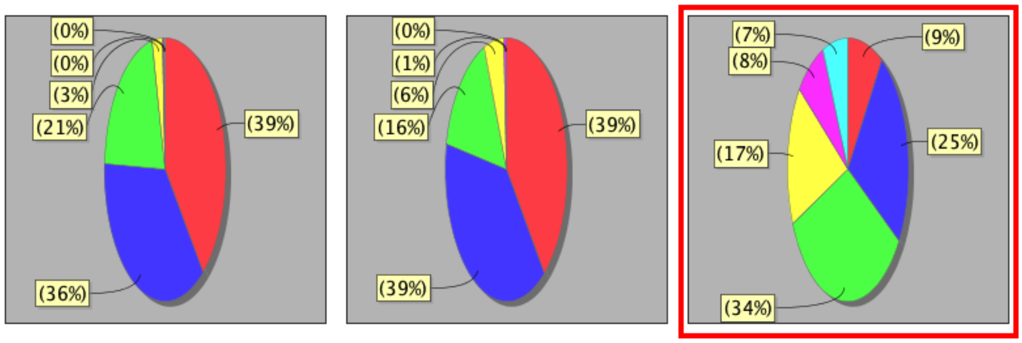
This simulation adds bicycle as congested mode. This simulation corresponds to MATSim with multiple congested modes not following FIFO as mentioned in Sec. 5.7.

Fig. 8c compares the real count data vs. simulation count data for average weekday traffic volume. This comparison validates the results generated from MATSim as mostly points fall nearly equal count line.

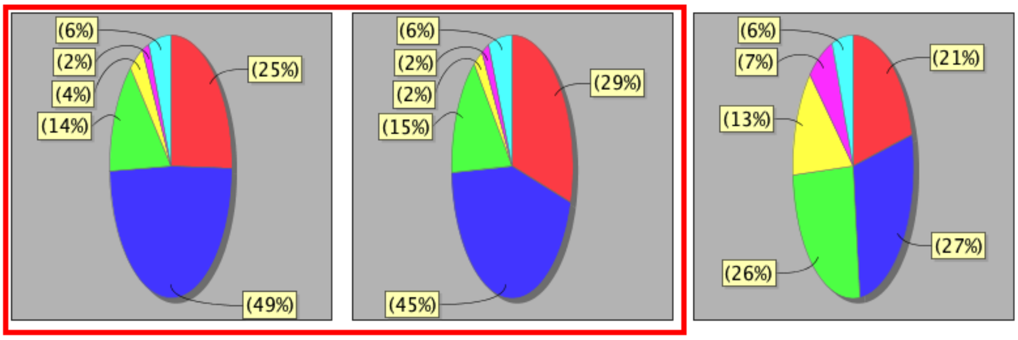
Fig. 7d shows the travel time distributions of the combined car/motorcycle/bicycle simulation. All three congested modes have large shares of travel times above 60 min. This is unrealistic: although we do not have the travel time distribution by mode for Patna, Fig. 1b shows the overall travel time distribution presented in iTrans (2009), based on the primary survey. According to that distribution, trips having a travel time more than 60 minutes are very few. In addition, the average travel time from simulation is more than 55 minutes for cars and motorcycles and about 70 minutes for bicycles, compared to 21.43, 18.56 and 19.94 in Table 1. Overall, the number of trips having large travel times is too high. This can, in part, be traced back to the bicycle-only simulation (Sec. 6.2): Even with only bicycles using the full flow capacity of the network, travel times were fairly high. This has now become even worse (comparing the bicycle plot of Fig. 7b with the bicycle plot of Fig. 7d). One interpretation at this is that, using the design numbers from the Indian Road Congress (IRC-11, 1962; IRC-106, 1990), the capacity of the network is insufficient to carry the demand. Another interpretation is that the model choice, as performed by the initial demand generation, is too inflexible, and allocates in particular too many long trips to bicycle.



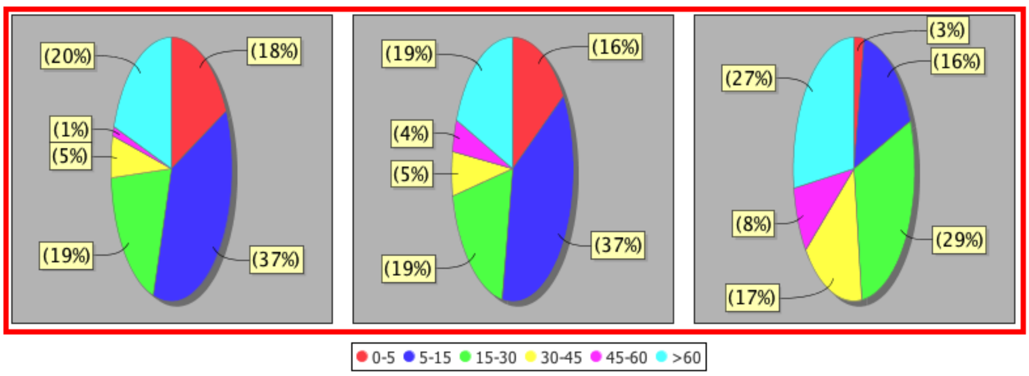
(a) Congested mode car



(b) Congested mode bicycle

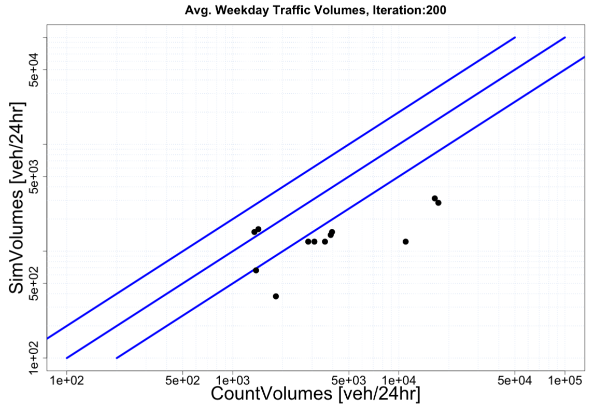


(c) Congested modes car and motorcycle

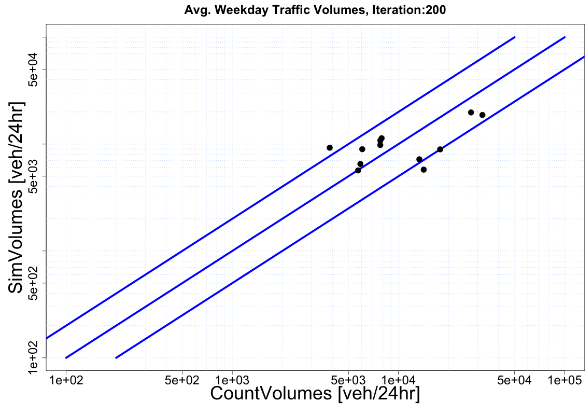


(d) Congested modes car, motorcycle and bicycle

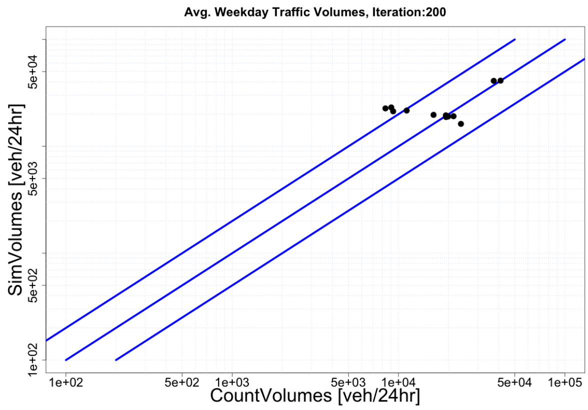
Figure 7: Distributions of travel time (in minutes)



(a) simulation of car only, counts of car only



(b) combined simulation of car and motorcycle, combined counts of car and motorcycle



(c) combined simulation of car, motorcycle, and bicycle; combined counts of car/motorcycle/bicycle

Figure 8: Comparison of real count vs. simulation count for iteration 200 when mode choice is disabled. Log-log curve between count volume and sim volume.

7. Patna results with mode choice

In order to test the hypothesis that including mode choice would rectify some artifacts of the travel time distributions, mode choice was included into the simulation. That is, times, routes, and modes are now run as "innovative" strategies, until iteration 160. The remaining 40 iterations are run with only the (logit) choice model enabled, allowing the simulation to stabilize its choices and the corresponding scores (= experienced utilities).

In order to get the mode shares right, the MATSim utility function needs to be calibrated such that a mode share from real world data is replicated in the model. In the present situation, the simulation with car, motorcycle, and bicycle as congested modes was used for this purpose. Using our previous experience with situations where no value-of-time survey was available, we first set the (dis-)utility for traveling for all modes to zero. This means that travel is penalized only by the opportunity cost of time, with an approximate (linearized) value of $-6/h$. Alternative-specific constants are then used in order to obtain the desired mode share. The resulting constants are displayed in Tab. 3. They are quite plausible: walk and bicycle normally have no initial impedance, car and public transit (PT) often have some initial overhead either in terms of getting the car out of the garage or in terms of walking to public transit, and motorcycle is in between.

The simulations were re-run for all situations described in Sec. 6. This was done in order to gain insight for each configuration in how far mode choice as additional choice dimension would influence the results. The mode choice

Table 3: Mode specific properties

Case	Car	Motorcycle	Bicycle	PT	Walk
Mode choice from Patna CMP	2%	14%	37%	18%	29%
Mode choice from trip diaries	4.11%	21.14%	33.25%	21.95%	19.55%
Mode choice after calibration	2.07%	13.88%	37.02%	17.87%	29.16%
Alternative-specific constants	−3.3	−2.2	0	−3.4	0
average tip time from ...					
... Patna CMP	21.43	18.56	19.94	n/a	19.28
... simulation w/o mode choice (Sec. 6.4)	58	61	70	13	35
... simulation w/ mode choice (Sec. 7.4)	17	12	19	20	16

parameters (mode-specific utility functions) were left as described above for all runs.

7.1. *Congested mode: car*

Even for car as the only congested mode, the results look quite different (Fig. 9a) than before: The travel times for car and motorcycle in the average get longer, while for bicycle they get shorter. Thus, even the "teleported" modes motorcycle and bicycle react to mode choice. The reason is that the mode choice model now prefers car and motorcycle for longer trips, and bicycle for shorter ones. Clearly, even the teleported modes react to this, since shorter trips means shorter beeline distance and thus shorter travel times even when these modes are not simulated on the network.

Fig. 10a shows the comparison of average weekday real count vs. average weekday simulation count for iteration 200.

7.2. *Congested mode: bicycle*

When having bicycle as the only congested mode, the travel times by bicycle increase (Fig. 9b) compared to the teleported variant. The travel times by (teleported) motorcycle remain the same as before. Somewhat surprisingly, the travel times by teleported car increase when compared to Sec. 7.1 (Fig. 9a). Presumably, the teleported car speed is much lower than the network car speed obtained in Sec. 7.1 – which is, in fact, quite plausible, since Sec. 7.1 is effectively run with free speed travel times while the teleported speed includes the effect of average congestion.

7.3. *Congested modes: car and motorcycle*

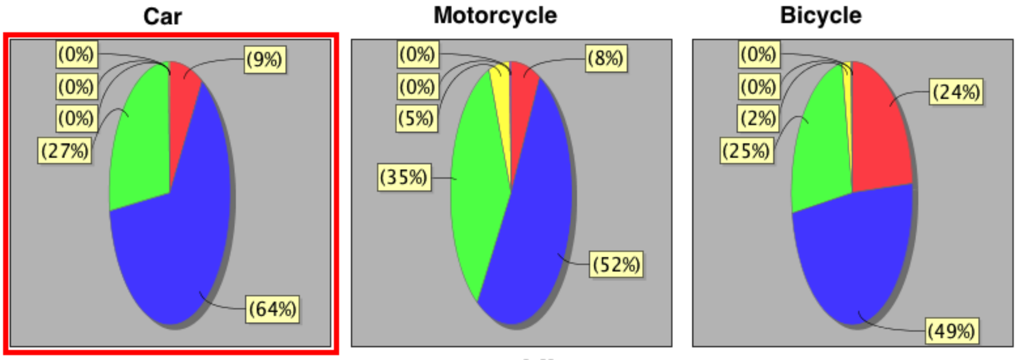
When having both car and motorcycle as congested mode, the average travel times by car and motorcycle increase, while the bicycle travel times revert to the teleported travel times (Fig. 9c). That is, in spite of the increased travel times for the motorized modes, these trips to not shift into bicycle in large numbers. Compared to the results without mode choice (Fig. 7c), the travel times in all modes are considerably reduced; in particular, the segments above 45*min* are not even visible any more.

The comparison to counts is shown in Fig. 10b.

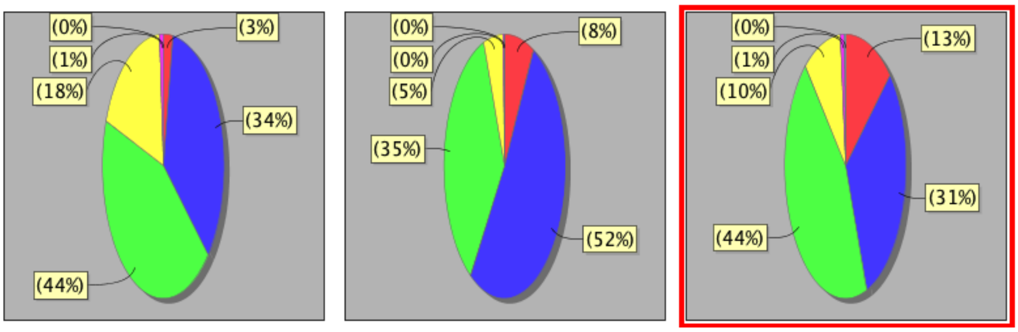
7.4. *Congested modes: car, motorcycle and bicycle*

Finally, Fig. 9d displays result when having car, motorcycle and bicycle as congested modes, when passing is allowed. The average travel times per mode are also given in the last row of Tab. 3. They are now much closer to reality than before. Thus, somewhat surprisingly, enabling mode choice has not only reduced the share of the bicycle trips with overly long durations: Also car and motorcycle trips with overly long durations got reduced very much. This is a bit surprising, since moving long trips from bicycle to car/motorcycle while moving shorter trips the other way should have *increased* congestion. Presumably, the longer trips are now able to use the bypass roads, and are thus able to drive around congestion much more than before. This seems to warrant additional investigation.

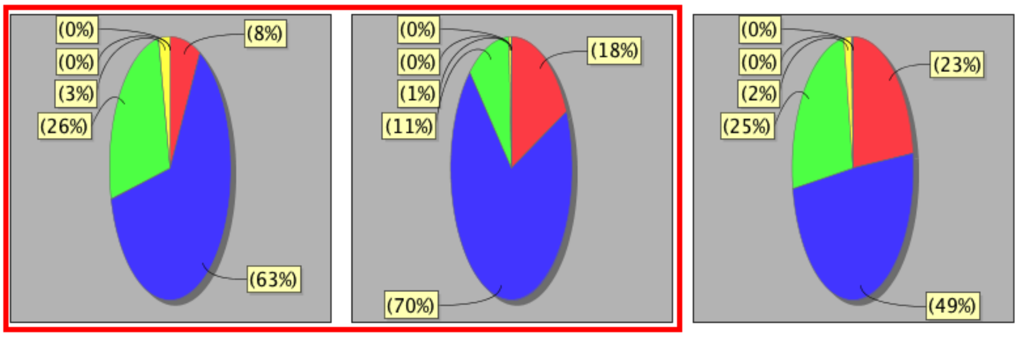
The comparison to counts is shown in Fig. 10c. The plot demonstrates that the comparison to counts does not decline when mode choice is enabled.



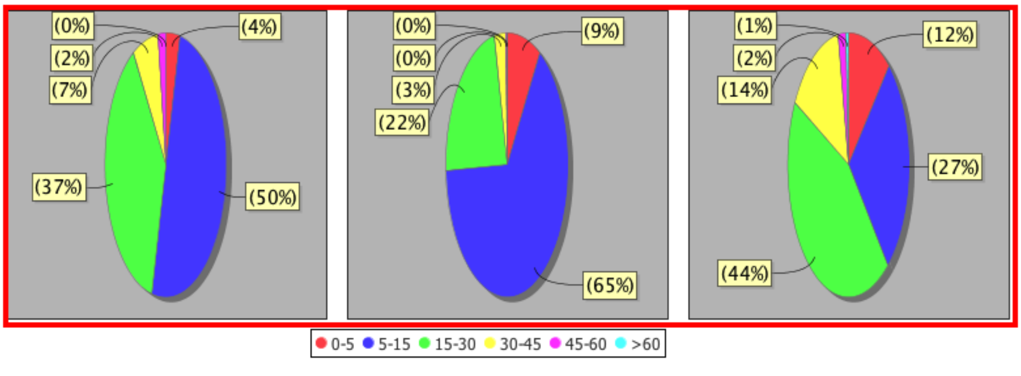
(a) Congested mode car



(b) Congested mode bicycle

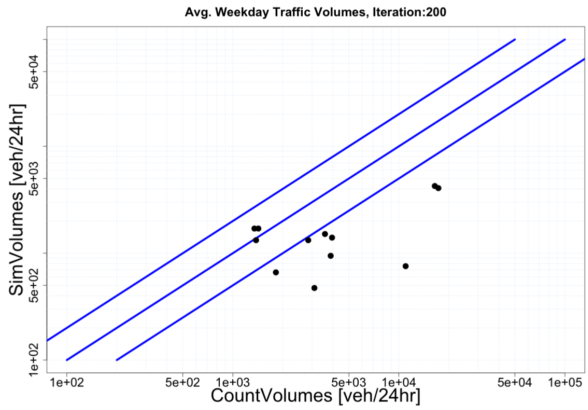


(c) Congested modes car and motorcycle

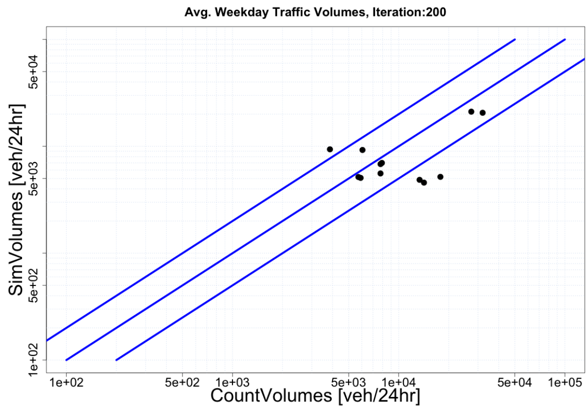


(d) Congested modes car, motorcycle and bicycle

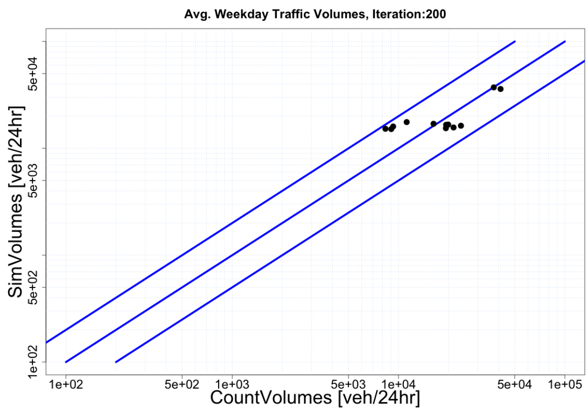
Figure 9: Distributions of travel time (in minutes)



(a) simulation of car only, counts of car only



(b) combined simulation of car and motorcycle, combined counts of car and motorcycle



(c) combined simulation of car, motorcycle, and bicycle;
combined counts of car/motorcycle/bicycle

Figure 10: Comparison of real count vs. simulation count for iteration 200 when mode choice is enabled. Log-log curve between count volume and sim volume.

8. Discussion

Although the results from the simulation are not matching exactly the results in the primary survey, they are similar enough to explain the Patna traffic so that the simulation could be used for scenario analysis.

Based on the existing comparison to real data, the main shortcoming of the present model seems to be the overly small average travel time of motorcycles. Since motorcycles have the same speed characteristics as cars, this is presumably due to the smaller alternative-specific constant, which allows to switch from the short-distance modes walk or bicycle at shorter distances than with car. Overall, however, the available (beeline) trip distances are given by the survey. Thus, longer travel times for motorcycle could only be obtained with more congestion. In consequence, we conclude that including mode choice in the model has not only reduced congestion, but in fact seems to have reduced it a bit too much.

Overall, as mentioned earlier we find it somewhat surprising that enabling mode choice does not only reduce bicycle trips with overly long durations, but also reduced motorized trips with overly long durations. If these results can be substantiated with future studies, they would make a strong case for integrated simulations of all modes including, where appropriate, models of mixed traffic as investigated in the present paper.

9. Conclusions

This work provides a way to simulate modes other than car which could not be simulated earlier in a simple and computationally fast queue model. A new functionality is added to MATSim such that new vehicle types can be defined with their maximum speed and PCU (passenger car unit). This contributes towards the simulation of multiple modes, which is necessary for representing heterogeneous traffic conditions of developing nations.

Technically, this is achieved by inserting vehicles with different maximum speeds and different space consumption into the queue. These vehicles may or may not be following first-in-first-out approach. Based on the requirements, the simulation may replace the use of first-in-first-out approach in cases when passing is plausible by an approach where vehicles at the end of a link are sorted by their free speed link exit times. The approach shows plausible results as long as it can be assumed that the different vehicles cannot pass each other any more when there is congestion.

Overall, the investigation has shown that it is possible to apply microscopic, activity-based assignment also to mixed traffic conditions, while maintaining similar computational performance. This makes the approach useful for many areas where mixed traffic conditions are the rule.

Acknowledgements

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Appendix A. Effective queue Method

MATSim supplies only link enter (t_{enter}) and link leave time (t_{leave}) of each person. Therefore, following steps are used to calibrate queuing position $x(t)$ of each person on link.

1) Available free space on each link (l_{free}) is calculated by subtracting the effective cell size (c_{eff}) for all queued vehicles on link from link length (l). MATSim default cell size (c) is 7.5m.

$$c_{eff} = PCU * c$$

$$l_{free} = l - \sum c_{eff}$$

2) A vehicle is added to queue if present time (t) is more than required free speed travel time (t_{free}) on available free space (l_{free}) on link with free speed (V_{free}).

$$V_{free} = min(V_{link}, V_{vehicle})$$

$$t_{free} = \frac{l_{free}}{V_{free}}$$

where V_{link} is maximum speed on link and $V_{vehicle}$ is maximum speed of vehicle.

3) If vehicle is added to queue, queuing time (t_Q) is noted and free flow distance (d_{free}) is calculated using queuing time and free speed.

$$d_{free} = t_Q * V_{free}$$

Further, it is assumed that after queuing time vehicle travels with constant speed until it reaches at end of link.

4) Thereafter, for any person for first link, points $(0, t_{enter})$, (d_{free}, t_Q) and (l, t_{leave}) are plotted. Subsequently, distance traveled is summed up until it reaches the start of track (same link once again), where distance traveled becomes zero. This process is repeated for all persons.

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