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 modelling even more complex. Patna, the capital of the state of 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 agent-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 disaggregated, "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 disaggregated modelling, 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 engineer 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 illustrated 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 lanes.

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 dynamic traffic assignment investigation. Section 2 describes the MATSim framework, Section 3 demonstrates the data used for the study, Section 4 explains the modeling from the data, Section 5 introduces the modifications to the queue model and analyzes some of their properties with fundamental diagrams for traffic flow, Section 6 shows the results of the study and Section 7 concludes the study.

2. MATSim

The MATSim framework can be seen as 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 dimension of the road infrastructure, as well as information about the activities performed by the agents in the physical world. The simulation of the agents 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. Several strategies can be used; some of them are Time choice, Route choice, Mode choice, Destination choice, choice between already existing plans. When using more than one strategy, 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, only route choice and time choice are 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 as follows Ashok Rajpath, Old bypass and New bypass which are spread along the length of the city. 36% of roads 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, bus, 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 trip times for different population groups. More than 85% of people have a trip time less than 30 minutes.

4. Modelling

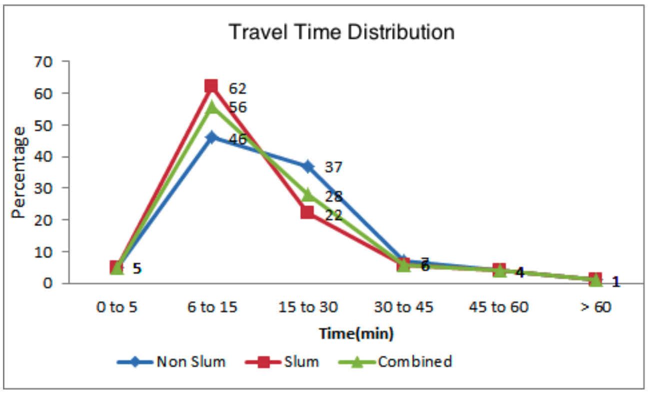
Patna network. To create a digital MATSim network for the Patna scenario, TransCad (TransCAD, 2011) files are used as input files. These files are a part of the data provided by iTrans (2009). [1] The hourly capacity is then computed according to Chandra and Kumar (2003) as

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

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.

[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.

(a) Road Network of Patna and 6 count stations



(b) Distribution graphs from Patna CMP. Source: after iTrans (2009)

Figure 1: Road Network and trip time distribution for Patna

Table 1: Average trip length, average trip time, mode share

mode	average trip 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%

Source : iTrans (2009)

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. The share of each mode is adopted from the overall mode share.

This results in 13,121 activity records, 10,110 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). For Patna, however, trips are distributed rather evenly between many modes. In order to still have a sizable number of trips in each mode, the Patna population obtained from the survey is slightly expanded by a factor of two. This is achieved by "cloning" every person, and randomly shifting their locations and departure times slightly.

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 (DTA) iterations: in every iteration, 10% of travelers were given a new route that would have been fastest in the previous iteration. An additional 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; time mutation was switched off after 100 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).
- Synthetic persons who are not performing an activity are therefore implicitly foregoing that utility, resulting in a marginal opportunity cost of time of the same $6\,utils/hr$. If these synthetic persons are **traveling**, they incur an additional $-6\,utils/hr$ marginal disutility. This could be varied by mode, but is assumed to be the same for all modes here (`travelingCar, travelingBike, ...`).
- Bicycles incur an additional marginal (dis)utility of **distance** of $-0.01\,utils/m$ as a proxy for the physical effort (`marginalUtlOfDistanceBike`).
- Arriving **late** at work (after 11am, `activityLatestStartTime`) is penalized at a marginal rate of $-18\,utils/hr$ (`lateArrival`).
- Arriving **early** at work (before 7am, `activityOpeningTime`) is not penalized directly, but it is implicitly penalized by the opportunity cost of time (since, all other things being equal, the synthetic person could have started later for the trip, thus extending the previous activity and accumulating utility for that).

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 agents (26242 plans) in the simulation and total trip production (1.24 million trips; see Section 4). It is therefore set to 0.021.
- The **storage capacity** factor (`storageCapacityFactor`) is taken as three times of flow capacity factor (i.e. 0.063) 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 Section 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), but these are link parameters. 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 Section 5.6. The calculation of passenger car units is discussed in Section 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 without a registered vehicle type, 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 agent 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 replanning 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 of 0.5 and 0.75 for having 5% and 10% (and more) motorcycles in the traffic stream. Similarly for bicycles 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 have 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. Mallikarjuna and Rao (2006, 2011) calculated the PCU factor using area occupancy. They used cellular automata model. However, also their area occupancy is affected by speed and thus cannot be used here. The approach in the present investigation is, however, similar to these. 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 $q = \rho \times v$ where q is the traffic flow, ρ is density and v is the speed. This relationship does not hold true in complex traffic situations where the interaction between different vehicles increases. In the last decade, several authors have attempted to explain the different states of the traffic flow by varying several parameters. Jost and Nagel (2003) discuss the different phases and states of traffic flow and phase transition. Kerner (2004, 2009) explains the three phase traffic theory and its applications in detail. Li et al. (2010) studies the phase diagrams with varying fraction of faster and slower vehicle mix. Hong-Wei et al. (2011) investigates dynamics of the motorized vehicle with non-motorized vehicle.

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.

To generate FDs, a test scenario is considered with a simple network in the form of a race track as shown in Fig. 2. 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

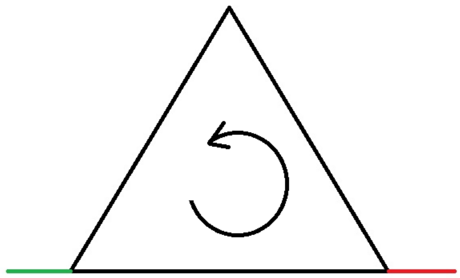


Figure 2: Simple network used for generating the fundamental diagrams

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 3 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

Fig. 3 shows 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 constantly 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.

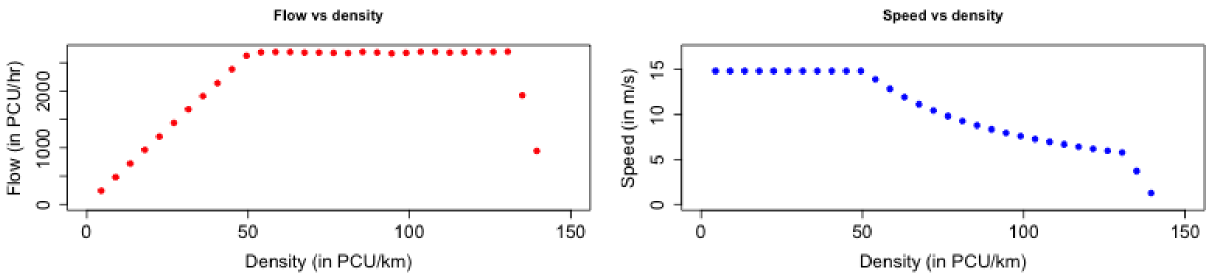
Fig. 3b is for bicycles only. In this case, flow grows linearly with density, up to a value smaller than the maximum flow capacity of the link, and then abruptly drops. The reason is as follows: Free speed determines the rate of the linear increase in flow in the laminar regime. For a lower free speed,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

5.6. Mixed traffic without passing

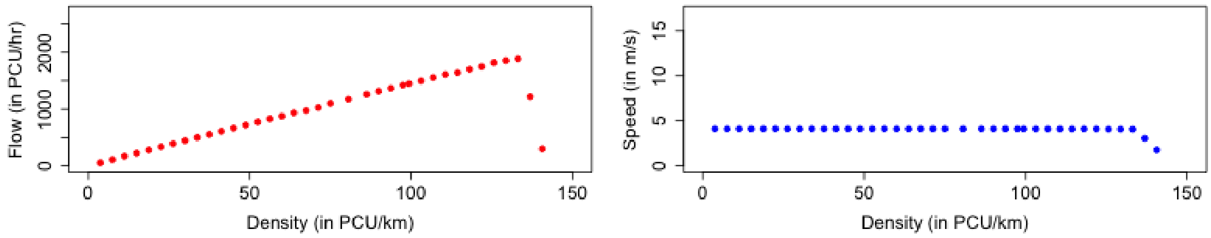
In Section 5.1 it was pointed out how the single congested (network-simulared) mode could be chosen. It is, however, plausible to assume that for Patna having only one of the modes as congested will not be sufficient, thus interactions between modes need to be included.

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 does not account for vehicles passing each other, the vehicles remain in First-In-First-Out (FIFO) order.

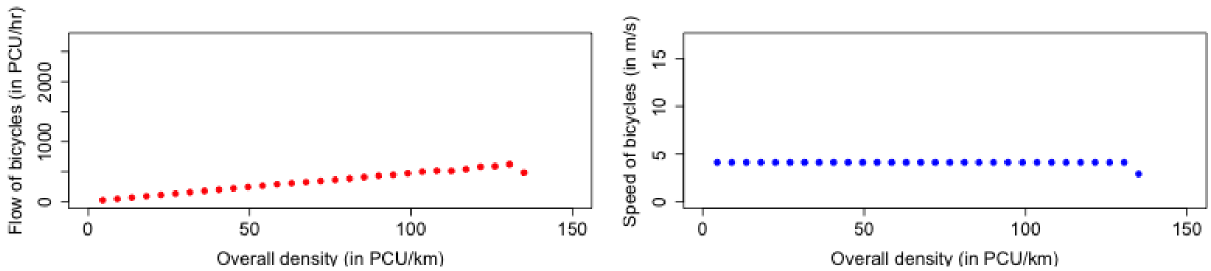
In order to explore the flow characteristics in such scenarios, vehicle types having substantial difference in their speeds are simulated on the test track. Fig. 3c shows FDs when car, motorcycle and bicycle are simulated. Equal



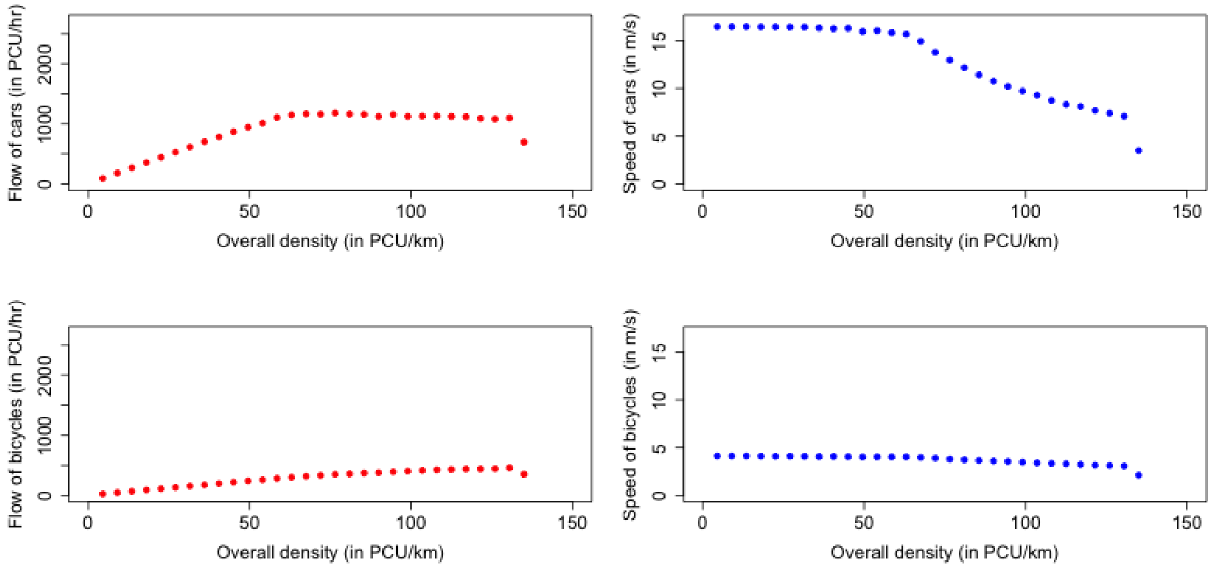
(a) FDs for simulation runs where only cars are on the network. Repeating this for motocycles gives identical results.



(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 are identical to plots for car (shown here).

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

modal split is used (1 car, 4 motorcycles, 4 bicycles). Plots are identical 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 Section 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 the cars and motorcycles from Fig. 3, one obtains approximately the same plot as Figs. 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, 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 end of the link if it was only constrained by the maximum speed of the vehicle type and the link. 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 their 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).

Fig. 3d is obtained with cars, motorcycles and bicycles together, with equal modal split (1 car, 4 motorcycles and 4 bicycles). Speed of cars, motorcycles and bicycles are almost same as the respective free flow speeds till density reaches 60 PCU/km. At this point, the flow reaches about 1200 PCU/hr, 1200 PCU/hr and 400 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 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 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 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.

6. Patna results

The different ways of interaction between the modes described in the previous section were tested using the Patna scenario.

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 trip distances change much over the iterations (not shown). Also the departure and arrival time distribution (not shown) show no indication of congestion.

Fig. 4a 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 trip 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 trip 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 trip time distributions are therefore not shown.

Fig. 5a 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. As bicycles are driven by human effort, cyclists try to minimize distance traveled more than travel time. Therefore, the marginal (dis)utility of distance for bicycle is set to -0.01 $utils/m$ which means bicycle users are losing 10 units of utility for every kilometer that they travel. For comparison: they are losing 12 units of utility for every hour they are traveling – the addition of 6 units per hour opportunity cost of time plus an additional 6 units per hour spent traveling. In other words, the marginal (dis)utility of distance for bicycle is quite high, prompting bicycles to use short distances even when congested.

Fig. 4b 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 more than 80% of bicycle trips have a travel time less than or equal to 45 minutes.

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 (Section 5.6).

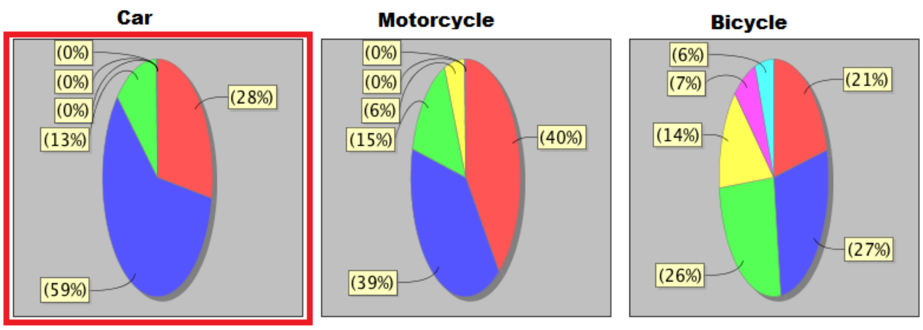
The leg histograms (not shown) show that all vehicles reach home again before midnight. However, a significant number of vehicles remains in the system until after 9pm, indicating congestion.

Fig. 4c represents the travel time distribution for all modes. Almost 90% of the trips of car users and motorcycle users have a travel time less than 45 minutes. The average simulated trip time for cars and motorcycles is almost same i.e. 20 minutes, while Table 1 shows average survey trip times for cars and motorcycles of 21 and 18 minutes respectively.

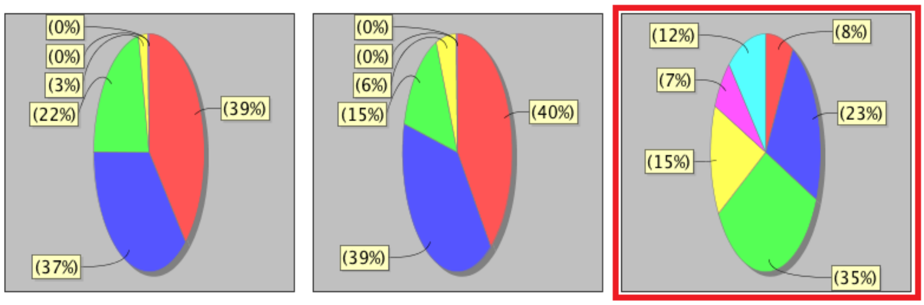
6.4. Congested modes: car, motorcycle and bicycle

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

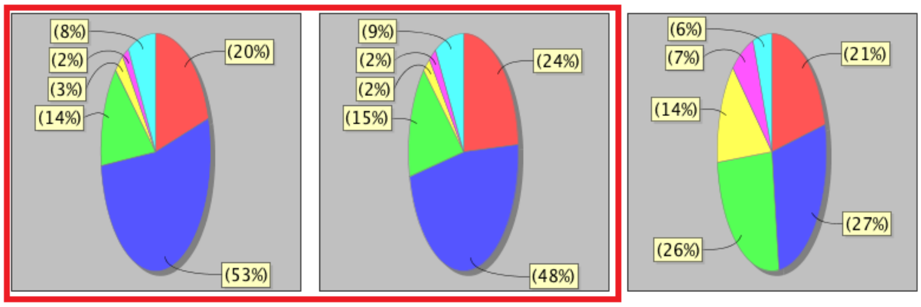
Fig. 5c compares the real count data vs. simulation count data for average weekday traffic volume. This comparison validates the results generated from MATSim as mostly points fall nearly equal count line.



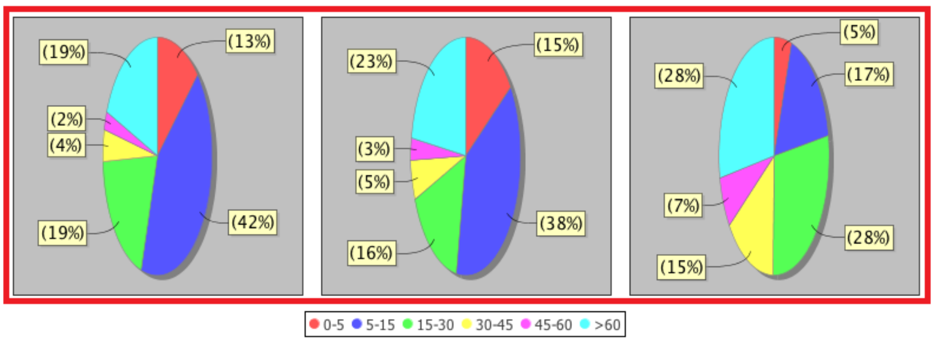
(a) Congested mode car



(b) Congested mode bicycle

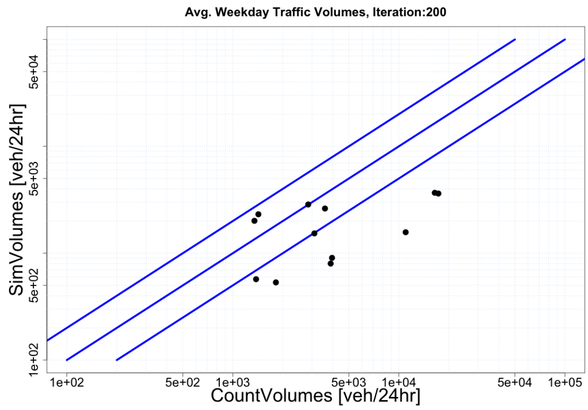


(c) Congested modes car and motorcycle

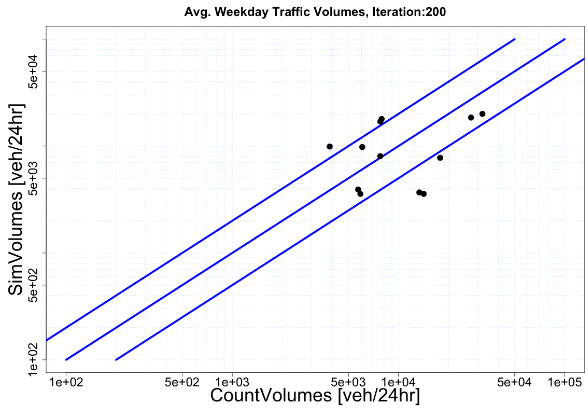


(d) Congested modes car, motorcycle and bicycle

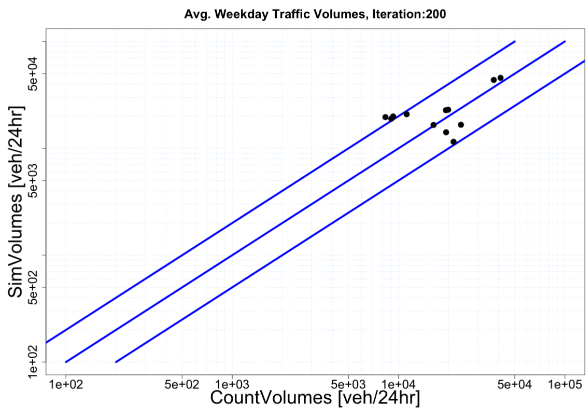
Figure 4: Distributions of trip time (in minutes)



(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 5: Comparison of real count vs. simulation count for iteration 200. Log-log curve between count volume and sim volume.

Fig. 4d 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 trip time from simulation is more than 50 minutes for cars and motorcycles and more than 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 (Section 6.2): Even with only bicycles using the full flow capacity of the network, trip times were fairly high. This has now become even worse (comparing the bicycle plot of Fig. 4b with the bicycle plot of Fig. 4d). The interpretation at this point 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.

7. Discussion

Overall, 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.

As stated earlier, the congestion levels generated by the bicycles seem to high. This is even visible when the bicycles use the full capacity of the roads, without competition from other modes. A reason may be that actual capacity in urban areas is larger than the numbers from the Indian Road Congress (IRC-106, 1990; IRC-11, 1962) for a given the road geometry. Another reason may be that in particular bicycle PCUs are too high, meaning that in reality the flow capacity of a car corresponds to more than four bicycles. As yet another possible explanation, the PCUs that one needs to insert into a queue-based simulation like MATSim may be different from the PCUs for static assignment models. Such an investigation was beyond the scope of the present study.

8. 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.

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