Congestion Avoidance in City Traffic

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Abstract: The number of vehicles on the road (worldwide) is constantly increasing, causing traffic jams and congestion especially in city traffic. Anticipatory vehicle routing techniques have thus far been applied to fairly small networked traffic scenarios and uniform traffic. We note here a number of limitations of these techniques and present a routing strategy on the assumption of a city map that has a large number of nodes and connectivity and where the vehicles possess highly varying speed capabilities. A scenario of operation with such characteristics has not previously been sufficiently studied in the literature. Frequent short term planning is preferred as compared to infrequent planning of the complete map. Experimental results show an efficiency boost when single lane overtaking is allowed, traffic signals are accounted for, and every vehicle prefers to avoid high traffic density on a road by taking an alternative route. Comparisons with optimistic routing, pessimistic routing, and time message channel routing are given.

Keywords: vehicle routing, congesting avoidance, planning, traffic simulation, intelligent vehicles

1. Introduction

Large numbers of vehicles within a road network commonly give rise to congestion which is marked by a large drop in the average speed of the moving vehicles. As a result every vehicle takes a considerable time to reach its final destination. On a particular road, congestion may be recurrent or non-recurrent (Gordon, 2009). While regular drivers are normally prone to adjust their departure times and routes for recurrent traffic, non-recurrent traffic congestion is hard to predict and adjust to. Non-recurrent congestion is caused by unusually high demand (like a sporting event) or suddenly low capacity (like an accident or a road closure).

An increasing amount of autonomy in vehicles and transportation management systems has given impetus to the possibilities of congestion avoidance. While it is possible to locate, track, and measure traffic density on various roads by intelligent agents concerned with road infrastructure (Ma et al., 2009), intelligent devices in vehicles are capable of collecting live data and using the same for planning purposes (Bishop, 2000; Reichardt, et al. 2000; Zito et al., 2011). This makes it possible to enable a vehicle to avoid roads where congestion is likely to occur and to use alternative routes.

Traffic congestion (Verhoef, 1999; Maniccam, 2006) may be avoided to a large extent by routing techniques, which tell the vehicle the route they need to travel. Presently installed devices and systems like SatNav only take static data. Unfortunately this results in multiple vehicles using the same roads, which leads to congestion.

In this paper we firstly analyze the true state of the traffic system with an eye on possible future developments, and assume a traffic scenario which we find prone to traffic congestion for everyday travel. Henceforth referred to as the city traffic scenario, we analyze this traffic scenario and proceed to make a traffic routing strategy for the guidance of vehicles. Experimental results are performed on the city (town as per local terminology) of Reading, United Kingdom. We show how the proposed approach considerably improves on the approaches presently reported in the literature for the stated scenario.

The work reported here carries forward the concept of having a transportation system with vehicles which have diverse speed capabilities from an earlier work of the authors (Kala and Warwick, 2013a). However while the aim of (Kala and Warwick, 2013a) was to construct a trajectory planning algorithm for autonomous vehicles travelling in unorganized traffic within a straight road segment, this work is aimed at studying the effect of diversity on the overall transportation system. Further this paper carries forward the concept from (Kala and Warwick, 2013b) wherein a vehicle may temporary lie on the ‘wrong’ side of the road in order to complete an overtaking procedure (henceforth referred as the single lane overtake). In (Kala and Warwick, 2013b) it was assumed that all the vehicles are autonomous and can communicate with each other to collaboratively formulate trajectories in traffic operating without lanes. In this work the concept is implemented without communication whilst assuming that the traffic operates in lanes. The aim is to study the impact on the overall transportation system.

The key contributions are: (i) Proposing city traffic as a scenario to study traffic congestion consisting of a large number of roads and intersections. (ii) Proposing a scenario of operation with diverse speed capabilities of the vehicles. (iii) Proposing a routing algorithm that eliminates the high density of traffic and hence minimizes congestion. (iv) Stressing frequent short term re-planning of the vehicle in place of long term (complete) infrequent re-planning.

2. Problem Formulation and Scenario of Operation

The problem of study is to move a number of vehicles in a map such that congestion is avoided. The vehicles must not violate any traffic rules. Every vehicle may emerge in any part of the map at any time. The origin, destination, or movement plan of any vehicle is not known by any other vehicle. This means there is a provision for manual vehicles in the traffic scenario. U-turns can only be taken from a traffic crossing and not in the middle of the road. The efficiency of this routing system is judged by the average time of travel of the vehicles. We consider this metric to reflect the magnitude of congestion that a vehicle faces during its travel. The algorithm is motivated by the characteristic scenario on which it operates, which we explain in greater detail in the following sub-sections.

2.1 City scenario

The scenarios of moving within a highway map and a city map are clearly different. Both however place stress on judiciously selecting the roads to travel on and forecasting the scenarios well in advance to avoid traffic congestion. But the former scenario has large length highways which, if entered, need to be followed for a significantly long time before an alternative path may be available whereas the latter has numerous alternative roads from which a vehicle may diverge and re-connect through any other close cut-in. The other point of difference lies in traffic emergence. Highway scenarios have distant entry and exits points, whereas in city traffic any vehicle can enter or leave from any road. Thus within a city, anticipation may not always help as it accounts for only recurrent traffic (in forecasting based systems) (Dia, 2001; Kirby, et al. 1997; Zhang and Liu, 2009), or intelligent vehicles which are on the road and whose travel plan is known (for anticipatory routing systems) (Weyns et al., 2007; Kaufman et al., 1991). In reality the vehicles may emerge from car parks (or homes) located at any point along any road and in doing so affect the entire network plan.

The difference between highway traffic and city traffic emphasizes the fact that while in highway scenarios it may be advisable to make long term plans, the same are not so useful for city traffic. In highway scenarios the vehicles can be expected to stick to their anticipated plans, thereby indicating which highway to follow. In city traffic, on the contrary, vehicles may make very frequent changes in travel plan due to the variety of options in terms of the roads to take to reach their destination. Since the number of vehicles is large, the total changes may be too large for any system to monitor and every change will affect all vehicles, which makes the system too dynamic to handle. Present approaches (e.g. Claes et al., 2011) limit the changes and only accept the changes which result in a significant improvement and hence control the highly dynamic nature of the problem in this way. Here we take part of the road map of Reading, United Kingdom as the city map given in Figure 1.

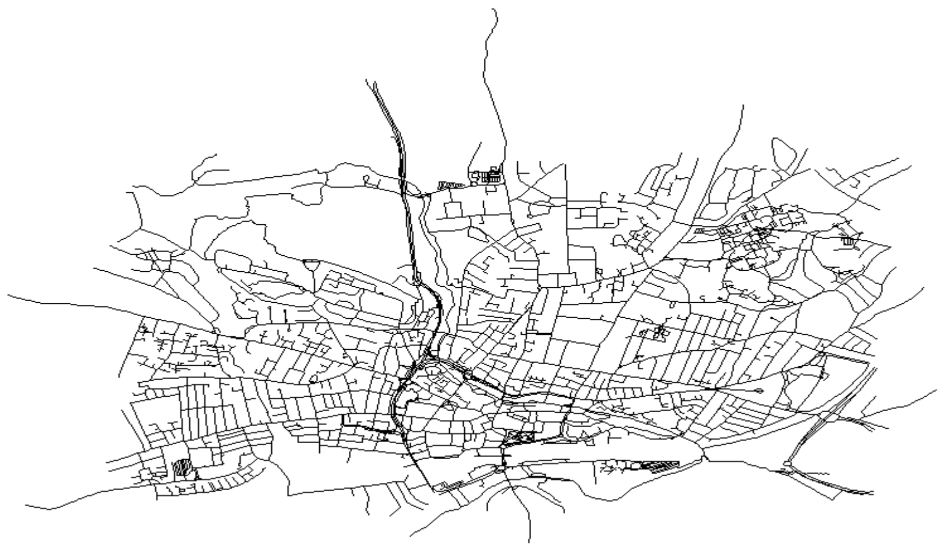

Figure 1: Map of Reading, UK used for experimentation

Routing may be classified into centralized approaches (Kuwahara et al., 2010) and decentralized approaches (Pavlis and Papageorgiou, 1999). Decentralized approaches consider every vehicle separately during plan generation and are hence able to generate a travel plan in a short time. During planning of each vehicle, decentralized techniques may prefer (i) not to account for another vehicle's motion, (ii) to predict the motion of other vehicles, or (iii) use traffic forecasting information from the historical data (Taniguchi and Shimato, 2004). Method (i) leads to high traffic congestion and method (iii) does not account for non-recurrent traffic. Microsimulation is a common tool for method (ii) wherein it is assumed that the travelling information of all the vehicles is available and the system operates by simulating the different possible plans. The method has limitations including the fact that it is computationally difficult to simulate a large number of vehicles for every re-plan of a vehicle's trajectory or in the case of any new vehicle entering. If a vehicle re-plans, the plans of some other vehicles may get affected and it may sometimes take a long time for vehicles to obtain their best plans. All vehicles on the road need to be intelligent and the assumption is usually that they have similar driving speeds. Also simulation uncertainties can become very large with time. These uncertainties are especially large when accounting for overtaking and traffic signals. All this puts an emphasis on long term plans being of less use for city traffic.

Whilst a high number of roads or high connectivity leads to a significant variety of travel options, it further makes the problem computationally expensive. Cities are normally large. Most studies are restricted to traffic over only part of the overall city map.

2.2 Inferred Hypothesis

Understanding the stated points we note here that it is important to make *frequent effective short term plans*, rather than making plans which are too long term, investing in heavy computation and hence limiting the planning frequency. From a simulation tool perspective, the computing infrastructure that simulates, renders, and moves every vehicle is limited and it has to give simulation results within limited times. As a result researchers usually have to limit the frequency of re-planning for each vehicle and this has a considerable impact on the study.

From the perspective of a physical system every vehicle has its own computing infrastructure which interacts with the other computing infrastructures to get information. In a scenario where the static map is itself complex, loading the vehicle with excessive information on the motion of the other vehicles makes the computing even more difficult. This is of less use when considering that long term plans are uncertain and hence the real/actual information is likely to change.

2.3 Other Scenario Specifics

Traffic systems in most countries consist of vehicles which travel with nearly the same preferred speeds. However we aim our study at scenarios where the vehicles may greatly differ in their preferred speeds (Kala and Warwick, 2013a). The difference in present day traffic mainly reflects the urgency, driving capability, and experience of the drivers. Technology has led to modern day vehicles to be classified as autonomous, semi-autonomous or manual vehicles. In the first two we may see in particular vehicles that differ in speeds as per size, price, features, sensing and control algorithms. As an example, Indian traffic already has vehicles with distinctly diverse speeds which are normally related to the type of the vehicle, ranging from saloon car to lorry or auto-rickshaw.

Considering city based traffic, we further consider a major proportion of the roads to be 2 lanes with 1 lane each for inbound and outbound traffic. With diverse speed it is naturally unpleasant for a high speed vehicle to be following behind a low speed vehicle for a large part of the journey, where there is no multi-lane to overtake by lane changes. Hence we allow here for vehicles to travel on the 'wrong' side of the road for some time so as to complete an overtaking operation (Kala and Warwick, 2013b).

2.4 Decentralized Anticipatory Routing

A significant attempt is made in this paper to use a decentralized anticipatory approach to vehicle routing. In a recent work Claes et al. (2011) presented a system wherein every vehicle considers all possible routes before selecting a 'best' route for its journey. The authors realised a formula to convert the anticipated traffic density into an average travel speed. This extends the work of Weyns et al. (2007) who used traffic microsimulation to compute the anticipated traffic speed. Re-planning is done after some time steps for every vehicle. In light of the discussions we summarize the limitations of the approach to be too in-frequent re-plans, the impossibility of computing every possible route in real time for large maps, the assumption that every vehicle is intelligent, no consideration given for traffic lights or overtaking and finally all vehicles are assumed to have the same preferred travel speed which makes conversion of traffic density to predicted speed possible. Most of these limitations might however hold if the complete map was itself small.

Our attempt is to present a fairly simple system not making assumptions which may not hold true in the real world. In section 4 we show how this may lead to a better performance in city traffic. In fact the complete system may be implemented by the adoption of a simple changeable message sign (CMS) at every road end, along with some detectors (such as an array of loop detectors, a counter for vehicle entry/exit, etc.) to measure traffic density (Sone, 1994; Summer, 1994).

3. Proposed System

3.1 Traffic Simulation

Vehicle motion is done using an Intelligent Driver Model (Treiber et al., 2000). The model states the manner by which one vehicle follows another vehicle depending upon the preferred driving speeds, operational speeds and available separation distances. The preferred speed of the vehicle V travelling along road R_{ij} connecting nodes v_i and v_j is taken to be $vpref_{ij} = min(s, speed\_limit_{ij})$, where s is the preferred speed of the vehicle V. $speed\_limit_{ij}$ is the maximum allowable speed on the road R_{ij}. Since the road traffic is diverse, the vehicles vary in their maximum speed s.

Considering a high diversity, a lot of overtaking is possible solely by lane change mechanisms. Hence a vehicle must always be ready to overtake a slow vehicle in front, and to itself be overtaken by an even faster vehicle to the rear. For decision making regarding lane changes, time to collision is used as a metric (if the vehicles continue to travel at the same speed).

If the vehicle is travelling close to its maximum speed limit $vpref_{ij}$ it may further attempt to stay in the left hand lane (in order to facilitate others to easily overtake it, in left side driving countries – UK/Japan style considered) unless it sees a slower vehicle ahead of it in the left hand lane. In such a situation naturally no question of overtaking arises whilst a vehicle to the rear has already requested to overtake. Overtaking on the right is preferred as compared to overtaking on the left in case both options are available and likely.

For simulation purposes, traffic lights are assumed to be intelligent in that they know the magnitude of vehicles at each entry point and their time of arrival. The traffic lights do not change in a cyclic manner, but allow traffic to flow from the direction of the vehicle with the longest waiting time. The switching frequency of the traffic lights is taken as a maximum of *mtim*. If there are no vehicles waiting to cross on the road whose traffic light is currently green and some other road has vehicles waiting to pass through, the traffic lights would change before the normal scheduled time. *mtim* is a constant and is set using simulations, such that it allows enough vehicles to pass through in a heavily congested traffic scenario. The factor is only of importance when there are far too many vehicles waiting to cross an intersection, as in other cases the queue clears well before this factor comes into play. Complete details regarding the traffic light operations can be found in Kala (2013).

3.2 Single lane overtaking

In case the vehicle is travelling on a road where there exists a single lane for each side of the traffic, it may be undesirable to follow a slower vehicle in front. Hence the vehicle is allowed to move onto the wrong side of the road in order to overtake the slower vehicle and to then return to the left hand lane (Kala and Warwick, 2013b).

For overtaking it is essential that the vehicle being overtaken is travelling almost at its preferred speed which is slower than the preferred speed of the overtaking vehicle. Also the vehicle being overtaken must itself not currently be overtaking another vehicle, and any other vehicle on the wrong side of the road (if any) must not be overtaking. An overtaking vehicle is projected to be accelerating till it reaches its preferred speed (or until overtaking completes) while overtaking. Separations from the vehicle being overtaken, to any vehicle on the wrong side of the road (if any), and the vehicle ahead of the one being overtaken (if any) are checked at every instance. All these must be greater than the preferred separations (as per the intelligent driver model) at all times during the overtaking procedure. Overtaking cannot happen if (by projections) it cannot be completed before the end of the road. If all the conditions hold good, overtaking then takes place. A synthetic overtaking scenario is shown in Figure 2. Complete details regarding the overtaking procedure can be found in Kala (2013).

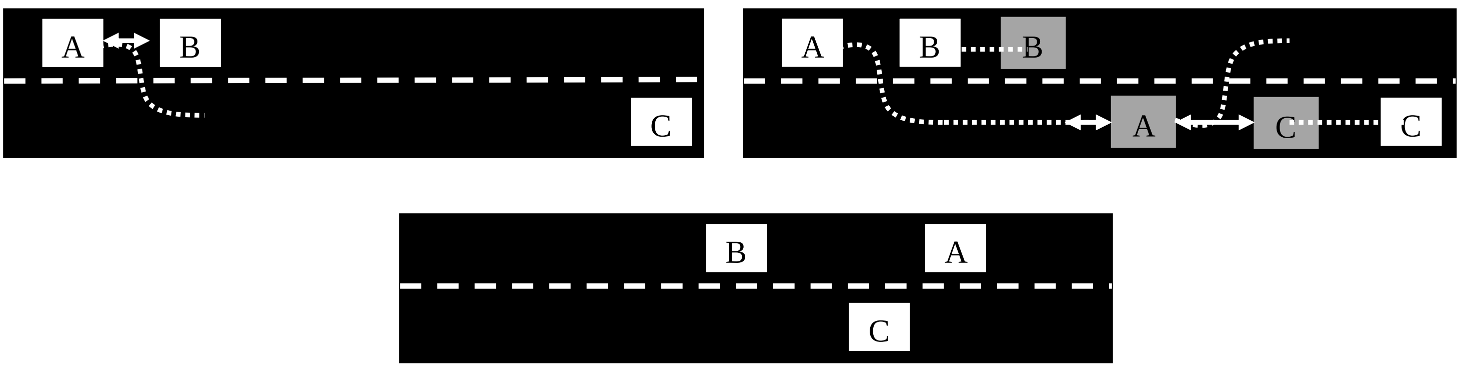

Figure 2: Single Lane Overtaking. (a) A checks feasibility to overtake B while C is coming from opposite end, (b) Projected positions of vehicles when A is expected to lie comfortably ahead of B, (c) Completion of overtake. Arrows indicate separation checks. Since A and C are moving in opposite direction, needed separation is much larger.

It may be interesting to observe that the applied overtaking mechanism assumes no cooperation with other vehicles. In simple words the other vehicles may assume that the overtaking vehicle is absent and move normally thereby still making the required separation with all the vehicles. The only exception is that other vehicles may not accelerate. In the real world the oncoming vehicle or the vehicle being overtaken may slow down as an act of cooperation. The important decision of whether overtaking is to take place is done solely by the overtaking vehicle without assuming cooperation, and even if an error is made the oncoming vehicle and the vehicle being overtaken compulsorily slow down to facilitate the overtake.

3.3 Vehicle Routing

Routing deals with the route selection of the vehicles. The frequency of planning is a key aspect which, as per the hypothesis, needs to be as large as possible for efficient congestion avoidance. Considering that it is not allowed to take a U-turn in the middle of the road, the earliest a vehicle can react to any change of plan is before a crossing. The planning should be done well-before reaching the crossing so that the required lane changes are made, traffic lights are read and suitable indicators are given before making the required turn at the crossing. Hence the maximum magnitude of re-planning corresponds to planning the vehicle before every crossing.

The basic planning algorithm employed is A* (Nilsson, 1980), which is a search algorithm and finds a path from a given source to a given goal depending on a cost function supplied in the solution design. The A* algorithm finds a solution by constantly expanding nodes with the best expected cost from the source to the goal. The historic cost $hist(v_j)$ of a node v_j refers to the actual cost from the source to reach that node as per the designed cost function. The heuristic cost $heuristic(v_j)$ on the other hand estimates the cost from the current node v_j to the goal. The algorithm searches by constantly expanding nodes based on these costs.

As per assumptions it is computationally very expensive to plan the entire route. We take our inspiration from the manner in which human drivers plan their route. Drivers can reach their destination by a simple attempt to select the roads that make the vehicle head *towards the goal*. In case multiple such roads are possible, short term planning may be done to reach some point by the best manner, beyond which an approximate travel cost may be assumed. However it is important to be assured that the selected point is actually connected to the destination, without having the vehicle to turn back or go by a long route. While doing so we certainly make the travel plan sub-optimal, but it is a compromise to the computational cost.

Hence the A* algorithm stops if the historical cost is more than *maxHistorical* and the current node (best in the open list) is termed as the goal, where the factor *maxHistorical* controls the computational cost. A low value of this factor makes the routing algorithm largely heuristic, where heuristic estimates determine the route; while a large value may be too computationally expensive. The factor is given the highest value as per the available computation. In the preliminary version of the algorithm a heuristic search (which is non-optimal but very fast) was used to ensure that the subsequent motion from the node does reach the goal without having the vehicle move backwards. However experimental results showed that such a path was always possible in the experimented scenarios and hence the check was removed, thereby saving on the computational cost. Having high connectivity it is natural that from any point the vehicle would be able to reach the destination by travelling towards it.

Let the historic cost of node v_j be given by $hist(v_j)$ and let e_{ij} be the average length of the road R_{ij} from node v_i to node v_j. The historic cost is given by (1). As the cost minimizes both the density at the road network as well as the number of traffic lights that the vehicle may encounter, the method is called *density based routing with traffic lights*.

$$hist(v_j) = hist(v_i) + \frac{e_{ij}}{S\left(vpref_{ij}, n(R_{ij})\right)} + \eta(R_{ij}).mtim(R_{ij}) \tag{1}$$

Here $S(vpref_{ij}, n(R_{ij}))$ is a function that predicts the average speed of a vehicle as per the current traffic scenario at the road R_{ij} having a current number of vehicles $n(R_{ij})$. In the present approach this is given by (2).

$$S\left(vpref_{ij}, n(R_{ij})\right) = \begin{cases} vpref_{ij} & n(R_{ij}) \le n_{th} \\ \dfrac{vpref_{ij}}{n(R_{ij})/k.n_{th}} & n(R_{ij}) > n_{th} \end{cases} \tag{2}$$

Here we assume the operating speed to be inversely proportional to the density. $\eta(R_{ij})$ is the fraction of traffic light changes that the vehicles at road R_{ij} wait for before getting a chance to get through the traffic lights. $mtim(R_{ij})$is the average time of wait at the traffic light for a single change. $mtim(R_{ij})$=0 if R_{ij} does not end at a traffic light. The factor n_{th} accounts for the number of vehicles that may leave within the traffic light change as per the factor $\eta(R_{ij})$, while the factor k relates density with the driving speed at dense traffic.

The heuristic cost is given by (3).

$$heuristic(v_j) = \frac{\left\| v_j - Goal \right\|}{\min\left(s, \max_{i,j}(speed\_\mathrm{limit}_{ij})\right)} \tag{3}$$

Here $\left\| v_j - Goal \right\|$ denotes the distance between the node v_j and the *Goal* measured using the coordinates of the two places on the road map. s is the preferred driving speed of the vehicle. The term $\max_{i,j}(speed\_limit_{ij})$ is the maximum speed possible on any road, which would point to the maximum allowable speed in the transportation network. Note that the heuristic function is admissible and assures optimality of the A* algorithm. However the expansion of the A* algorithm is proportional to the difference between the actual cost and the heuristic estimates (Russel and Norvig, 2010), which is high for the presented approach. This results in a significant number of nodes being expanded. The output of the A* algorithm is a *route* consisting of the roads that the vehicle must follow. A synthetic planning procedure showing the iterations of repetition is shown in Figure 3.

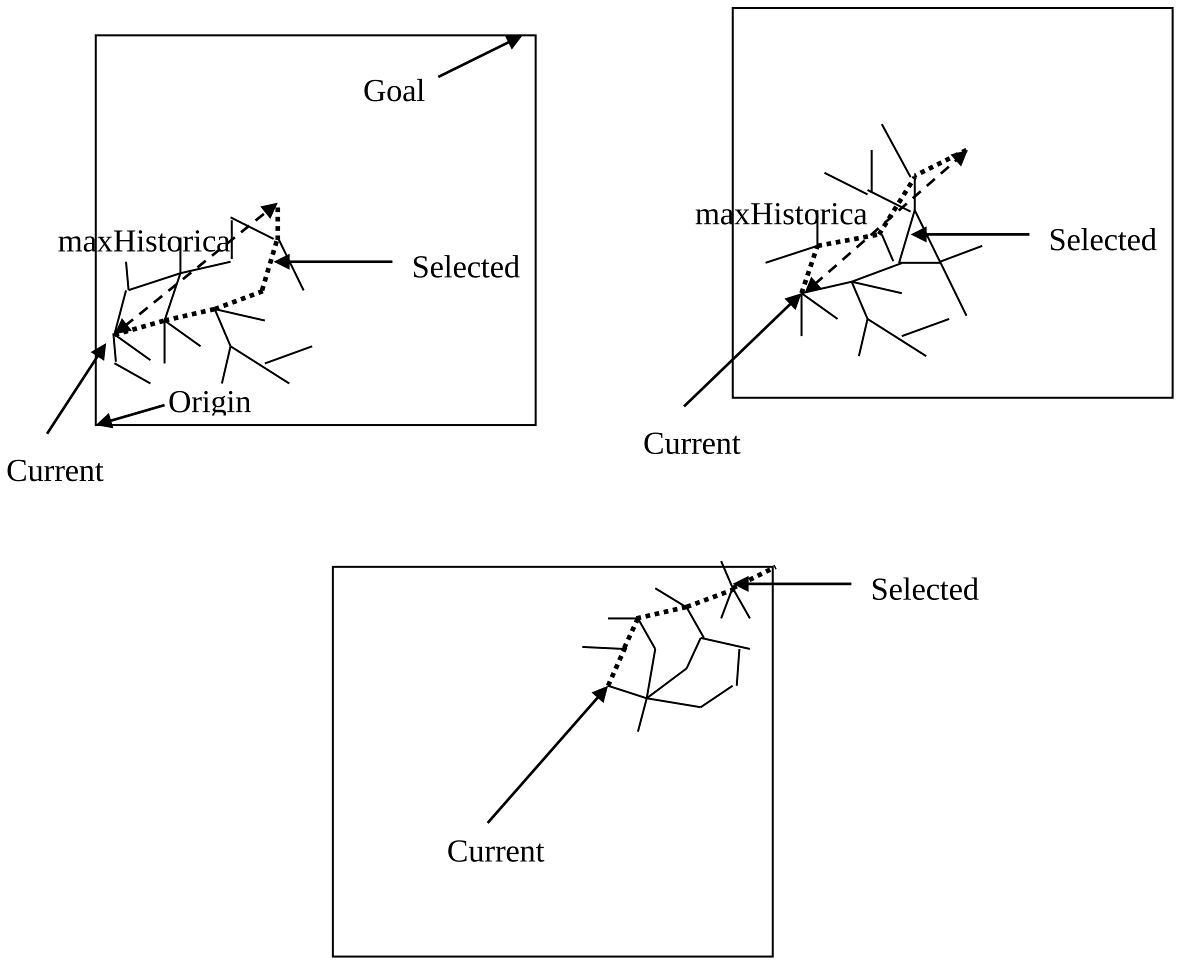

Figure 3: Routing by re-planning at every crossing. (a) From current position vehicle plans towards goal and after *maxHistorical* cost stops the current search and move by best path, (b) After reaching next crossing change of plan takes place as per new information available, (c) vehicle finally reaches a point from where the goal is near.

4. Experimental Results

4.1 Initialization

Experiments were done on a traffic simulator based on an intelligent driver model and other features as discussed in section 3. Experiments were done on a part of a road map of Reading, United Kingdom which is shown in Figure 1. The map was obtained from (Openstreetmap, 2012). A Depth First Search algorithm was used to eliminate isolated nodes. The processed map had a total of 7765 road nodes. Major roads were all assumed to be double lanes, while the general roads were all considered to be single lanes. Speed limits were fixed to 30 miles/hour or 40 miles/hour. The left side driving rule was followed.

Traffic is produced in the road network by randomly generating an original-destination matrix. The number of vehicles per second that enter the traffic scenario is taken as a human input using which vehicles are generated continuously for 10 minutes. Henceforth the generation of vehicles stops but the simulation runs till all vehicles reach their destinations. The origins and destinations are preferred to be on the opposite sides of the map separated by a displacement of more than the radius of the map. The origin is selected by using a Gaussian distribution with mean centered outside the map's central point by a magnitude of half the radius. The angle of origin to the map's center (θ) is chosen randomly. The destination is also chosen from a Gaussian distribution with mean at half the map's radius. The angle of destination to the map's centre is chosen from a Gaussian distribution with mean located at π+ θ. The speed limit of the individual vehicles is selected from a uniform distribution varying from 20 miles/hour to 40 miles/hour.

4.2 Alternative Methods

The strict constraint in the choice of the alternative methods for comparison was that no communication must exist between the vehicles or between all the vehicles and a central transportation system. Most research work on microsimulations, re-planning, etc. hence gets eliminated. Further since the approach is for non-recurrent traffic, most of the learning based systems get eliminated. Based on these assumptions there is a small choice of methods available, which were experimented on. There are however further issues relating to the diversity of the vehicles in terms of travel speeds which make many of the alternative methods unacceptable.

Comparisons of our technique have been carried out with a variety of other methods. Each basic method has two modes of operation, a static case wherein the route is planned initially and the same is followed un-altered till the goal is reached; and a dynamic case wherein the routing takes place at every intersection.

The first method employed is the optimistic fastest routing strategy used for static planning. The strategy computes a route by minimizing the expected time of completion of the journey, which is given by equation (4).

$$Cost(optimistic) = \sum_{e_{ij} \in Route} \frac{e_{ij}}{vpref_{ij}} \tag{4}$$

The second strategy used for comparison is the pessimistic fastest routing strategy which is similar to the optimistic fastest routing strategy with the difference that the cost to be minimized is given by equation (5). The attempt is to prefer roads which have a higher number of lanes. Here $w_{ij} = 1/lanes(R_{ij})$, $lanes(R_{ij})$ is the number of lanes in road R_{ij}.

$$Cost(pressimistic) = \sum_{e_{ij} \in Route} \frac{w_{ij}.e_{ij}}{vpref_{ij}} \tag{5}$$

The next strategy used is the Traffic Messaging Channel (Davies, 1989). In this strategy every vehicle on reaching the road segment end, informs the system about the average speed at the particular segment and this is used for planning other vehicles. Considering the simulation scenario, the cost minimized by this planning is given by equation (6).

$$Cost(TMC) = \sum_{e_{ij} \in Route} \frac{e_{ij}}{\min\left(TMC_{ij}, vpref_{ij}\right)} \tag{6}$$

TMC_{ij} is the average speed as known by the TMC system. The update is done as per equation (7).

$$TMC_{ij}(t) = \begin{cases} (1-lr).TMC_{ij}(t-1) + lr.v_{ij}^{avg} & v_{ij}^{avg} < vpref_{ij} - \varepsilon \\ TMC_{ij}(t-1) & otherwise \end{cases} \qquad (7)$$

v_{ij}^{avg} is the average speed of the vehicle at road R_{ij}, ε is a small number. Equation (7) avoids vehicles with lower preferable speed to slow the TMC known average values, if the actual traffic is moving reasonably fast. *lr* is the learning rate.

All these 3 strategies find the route from source to goal which does defy the assumption that the map is too complex for timely computing the route from the source to goal. This was however done only for comparative purposes. The time was large enough to disallow continuous re-planning.

The next set of alternative methods belongs to the dynamic domain where vehicles are re-planned at every crossing. Considering the computation time, in each case re-planning is done for short durations as explained in section 3.5. The 4 methods are experimented namely TMC, density, TMC with traffic lights and density with traffic lights. The last method is the proposed method as discussed in section 3.5. Density based planning is same except for the fact that it disregards the traffic light factor. The TMC method is the dynamic equivalent of the static TMC method. TMC with traffic lights has an additional cost on encountering traffic lights. The cost functions for each of these methods are given by equations (6), (8)-(10).

$$Cost(\text{density}) = \sum_{e_{ij} \in Route} \frac{e_{ij}}{S(vpref_{ij}, n(R_{ij}))} \qquad (8)$$

$$Cost(\text{TMC with traffic lights}) = \sum_{e_{ij} \in Route} \frac{e_{ij}}{\min(TMC_{ij}, vpref_{ij})} + \eta(R_{ij}).mtim(R_{ij}) \qquad (9)$$

$$Cost(\text{density with traffic lights}) = \sum_{e_{ij} \in Route} \frac{e_{ij}}{S(vpref_{ij}, n(R_{ij}))} + \eta(R_{ij}).mtim(R_{ij}) \qquad (10)$$

4.3 Comparisons

4.3.1 Average time of completion of journey

The metric that judges the effectiveness of the algorithm is the average time to destination. The results for increasing demands for various routing strategies are shown in Figure 4. The algorithm was tested for a maximum of 45 vehicles per second which meant that there were a total of 27,000 vehicles. The general trend expected was an increase in the average time of completion of the journey per vehicle, which is visible in the graph barring a few regions. The difference in trend is due to the fact that for every demand, different origins, destinations and speeds were selected.

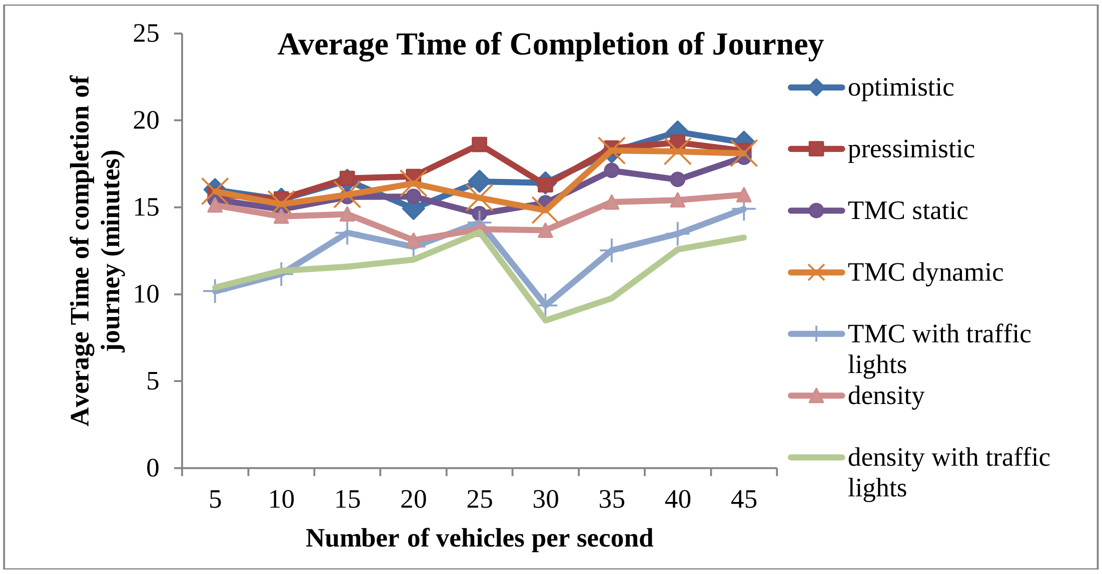

Figure 4: Average time of completion of journey for various algorithms and demands

From Figure 4 we can easily see that the proposed method performs best for all demands. The trend is closely followed by the TMC method with traffic lights. Clearly taking traffic lights into account was beneficial as density and TMC methods with the traffic light factor proved to perform better. An anomaly is the static TMC performing better than that the dynamic TMC. However while the static TMC invested heavily on computation at the start to find the best route from source to goal as per the set metric, the dynamic TMC plans only up to a point ahead. Hence restricting the search for computational betterment has a payoff for the algorithm when taking longer routes. Further, at higher demands it takes a little time for the traffic level to rise on the popular roads. Later vehicles prefer alternative routes, thereby keeping the congestion level the same or balanced. Since part of the city map was simulated, the static congestion level was enough information as it did not change much.

4.3.2 Average distance

While the time of completion of journey was the sole metric of use which was optimized, we also could see how the different routing strategies behaved in terms of total distance of travel. The graph showing the distance of travel for different demands is given as Figure 5. For large demands the proposed method had the shortest distance, while the largest distances were recorded by the optimistic and the pessimistic strategies. The distances for these strategies was largest due to the fact that faster strategies assumed roads with a high number of lanes and larger speed limits would lead to shortest travel time. These roads usually have a high degree of congestion and hence the assumption is incorrect.

The reason for longer time of travel for the dynamic TMC is visible in the distance graph which took longer routes. The TMC group of algorithms though had a better view of the applicable traffic speed. Density based methods taking shorter distances indicate the cooperative measure of vehicles in the front for vehicles behind, in case the main route important for the vehicles behind is congested. The algorithms including the traffic light factor show low distance indicating that it was precomputed that the majority of the time would be wasted at traffic lights.

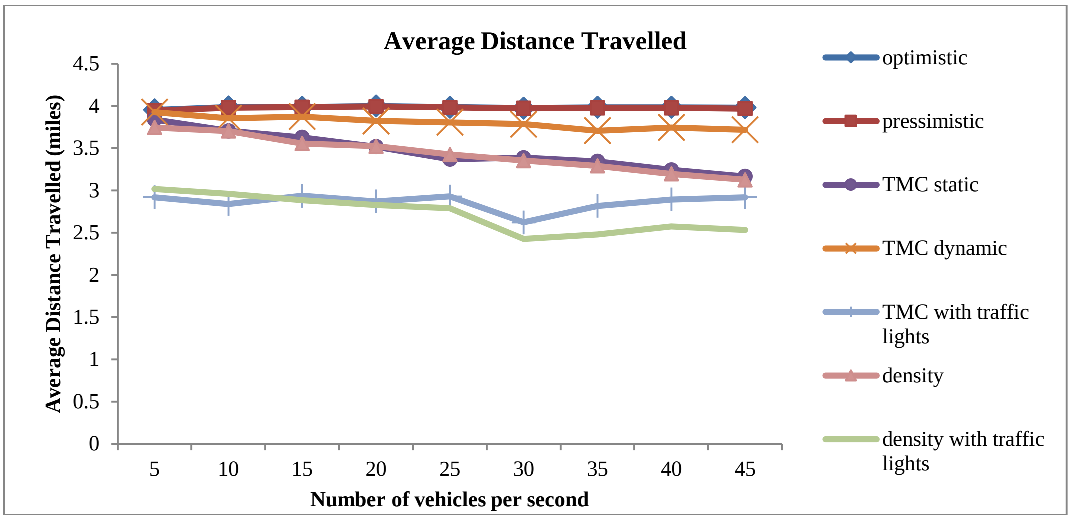

Figure 5: Average distance travelled for various algorithms and demands

4.3.3 Average speed

The travelling speed is simply distance upon time, and hence it is fairly simple to understand. The trend for various algorithms is given in Figure 6. Considering that a significant portion of the time was wasted while waiting at crossings, the actual travel speeds were much higher. The optimistic and pessimistic algorithms emphasized taking wide roads which were longer, and hence the average speed was sufficiently fast even though it was reasonably less than the allowed speed limit. Other strategies emphasized taking shorter routes which were less congested and hence a decent travel speed could be maintained.

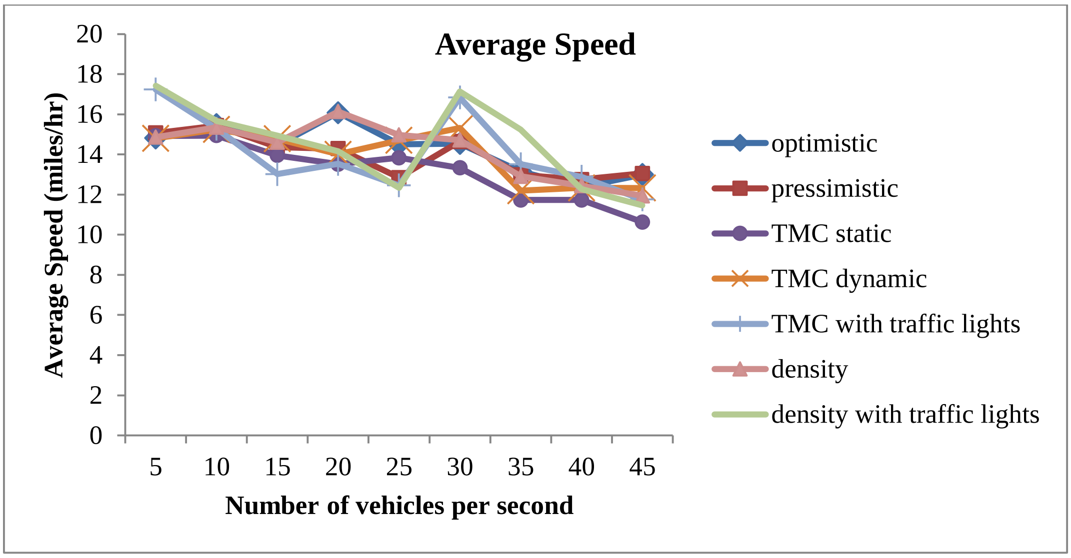

Figure 6: Average speed for various algorithms and demands

4.4 Analysis of Single Lane Overtaking

An important feature of the algorithm was the ability of having overtaking in single lane roads. Even if there is a single slow moving vehicle somewhere ahead in the lane, the entire lane traffic could suffer even in low congestion areas. Most roads being single lane make overtaking impossible without this feature. The average time of journey is shown in Figure 7. It can be clearly seen that single lane overtaking resulted in a great boost to travel time. Without the feature the main traffic scenario was primarily that all vehicles followed a slow vehicle ahead.

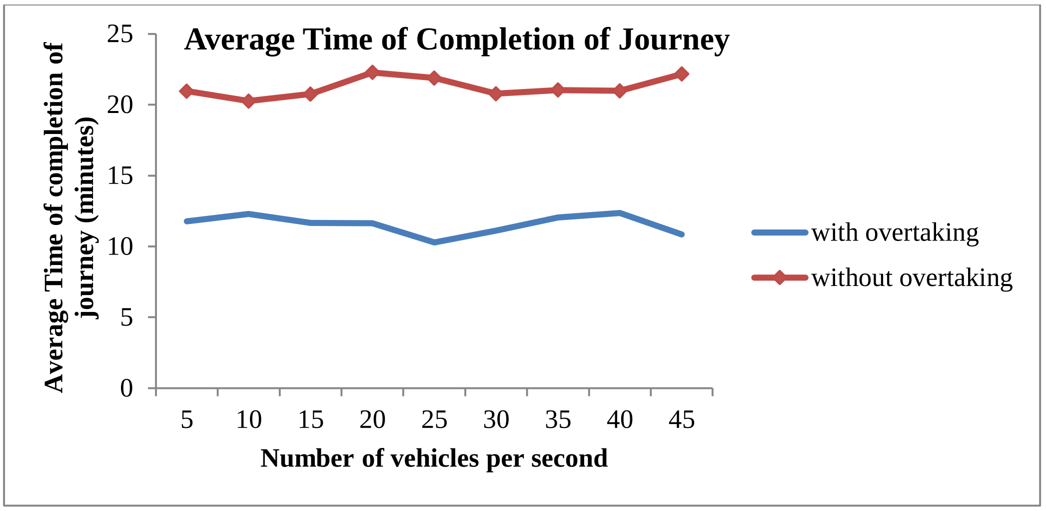

Figure 7: Average time of completion of journey with and without single lane overtaking

5. Related Works

In a situation where the number of vehicles is too large and the road infrastructure is limited, reservation seems to be a viable alternative. Congestion may be avoided by a careful reservation strategy. To the best knowledge of the authors a reservation based approach for the complete motion of vehicles is yet to be studied. Dresner and Stone (2004) studied a subset of this problem of intersection management and proposed a scheme where the autonomous vehicles could navigate by reservation irrespective of the traffic signal states. The authors further extended the model to incorporate learning behaviour and market economics of reservation (Dresner and Stone, 2006, 2007). Vasirani and Ossowski (2009) continued this work by presenting a market economy model for reservation. For roads an approach similar to reservation was used by Reveliotis and Roszkowska (2011) who modelled the entire road infrastructure as resources with a judicious resource allocation algorithm.

Another realization of the problem is to view the complete road network graph as a Markov network with the route as a Markovian process. Kim et al. (2005) presented their results to routing. The model could account for dynamic traffic and hence congestion could be monitored. Wahle et al. (2000) used Cellular Automata and defined various traffic behaviours like braking, accelerating, avoiding obstacles, etc. as rules. Based on this approach the authors showed a routing strategy so that the entire traffic was more distributed. In another related approach Furda and Vlacic (2011) also use Automata for system modelling. The authors exhibited vehicular behaviours including maintenance of position on the road, maintenance of a safe distance from other vehicles, collision avoidance, etc. Current behaviour was selected using Multi-Criterion Decision Making.

Inspired by the ant algorithms, digital pheromone is another popular mechanism by which traffic dynamics in a road network may be modelled and decisions may be made. Ando et al. (2004) represented various driving actions by a digital pheromone distribution. These pheromones gave an indication of traffic congestion. The same information was used for routing decisions. Narzt et al. (2007) also used the notion of digital pheromones. Their model used micro simulations with a decentralized routing strategy for vehicular motion.

In terms of route planning in a static sense, when the given road network graph becomes too complex, it is viable to use some hierarchical planning. Song and Wang (2011) employed heuristics to divide the entire road network into hierarchical communities. Each community marked a highly connected region. Li et al. (2009) represented a graph in a multi-layered approach with edges between the layers. Voronoi diagrams were used as the basis for hierarchical separation of the road network map. Tatomir and Rothkrantz (2006) presented another hierarchical approach. Their algorithm divided a road network into zones with identified road links connecting the zones. The authors used an ant based swarm algorithm to find the shortest route. In addition, the authors displayed how the time of journey may be computed when re-routing in accident situations.

Fawcett and Robinson (2000) displayed a system which monitored live data with relevance to the available road infrastructure and the mechanism by which this data may be made available to route planning of the vehicles. Kesting et al. (2008) looked at the problem of traffic congestion and proposed a model wherein vehicles could adapt their driving model parameters based on the available information of traffic flow.

Overtaking is another interesting phenomenon that has interested researchers. A vast number of approaches and strategies have been implemented regarding decision making for overtaking and for the generation of overtaking manuevours. Naranjo et al. (2009) presented one such approach where overtaking took place by a set of lane changes. A fuzzy based inference system was used. Another fuzzy approach to the problem exists in the work of Jin-ying et al. (2008). Hegeman et al. (2009) dealt with the problem of decision making regarding overtaking based on the separation between different vehicles. In a similar approach Wang et al. (2009) modelled the vehicle uncertainty and used the same to estimate possibility of collisions during overtaking.

6. Conclusions

In this paper we presented a method to solve the traffic congestion problem, accounting for the factors of traffic density and traffic lights for a city transportation infrastructure. The solution attempted to make frequent short term plans for each vehicle. The decentralized nature of the algorithm enabled its scalability. With this we also stressed the highly uncertain nature of long term plans based on which no decision making can be done. Experimental results show that the resultant algorithm outperformed all other commonly used algorithms. The algorithm performance was reasonably better when the vehicles were allowed to overtake in a single lane. Experiments showed that the traffic lights played a vital role in planning.

Any routing algorithm for vehicles has a strict decision point regarding preferring shortest path to goal, fastest roads or reducing the waiting time at crossings. Considering the nature of the problem where additional vehicles may pop up anytime and anywhere and known vehicles may change their plans without notice, it is impossible to predict these metrics for all roads. High diversity in terms of vehicular preferred speeds makes the choices even more difficult. Experiments show that the proposed algorithm is the best trade-off between these selections. Frequent re-planning ensures plans are adaptive to changing traffic.

Subsequent research may focus on formulating better predictors for travel speed and waiting time at a traffic signal for short term planning, modelling pedestrian traffic which may slow normal vehicular traffic, studying the effect of incidents on routing performance, better traffic light management systems and more cooperative overtaking mechanisms. Currently we do not have suitable data sets to train the routing algorithm parameters and this needs to be looked into, as well as a means to improve the traffic simulator, including implementation on a parallel computing cluster to obtain the results quickly. Hierarchical planning as well as a means to avoid getting into deadlocks (thereafter requiring turning back), especially by the use of contraction hierarchies will be studied in the future. Experiments involving different cities and larger highly interconnected maps may present more issues.

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