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Title: SIMPLE QUEUEING MODEL APPLIED TO THE CITY OF PORTLAND

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Simple queueing model applied to the city of Portland

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Abstract

We present a simple traffic micro-simulation model that models the effects of capacity
cut-off, i.e. the effect of queue built-up when demand is exceeding capacity, and queue spill-
back, i.e. the effect that queues can spill back across intersections when a congested link
is filled up. We derive the model's fundamental diagrams and explain it. The simulation
is used to simulate traffic on the emme/2 network of the Portland (Oregon) metropolitan
region (20 000 links). Demand is generated by a simplified home-to-work assignment which
generates about half a million trips for the AM peak. Route assignment is done by iterative
feedback between micro-simulation and router. Relaxation of the route assignment for the
above problem can be achieved within about half a day of computing time on a desktop
workstation.

1 Introduction

In transportation forecasting for planning applications, the generation of the transportation demand is crucial for useful forecasts. Activity-based demand modeling [1, 2] is a promising technology here. This means that one attempts to predict people's activities (work, shop, sleep, ...) and to obtain the transportation demand because activities at different locations need to be connected via transportation. Yet, it is clear that the *impedance* of the transportation system plays a critical role for activity patterns and activity locations. For example, high congestion may be an incentive to drop intermediate stops at home between activities, or it may be an incentive to do activities at home instead of somewhere else. Thus, a critical part of an activity-based transportation forecasting system is the representation of the transportation dynamics.

Any such approach needs to achieve "consistency" between modules. By this it is meant that the congestion assumptions on which people plan their activities need to actually be encountered when people execute their plans. Otherwise, people will adjust their plans in reaction to the traffic conditions they just found, and so the result is not stable and thus useless for forecasting.

This consistency criterion between planning and transportation dynamics can be formulated as a fixpoint problem [3, 4]. Fixpoints can, under certain conditions, be found via relaxation. In our case this means: make all plans; execute the micro-simulation with all plans; let (some or all) people change their plans according to the simulation result; etc.; until the simulation result is consistent with people's expectations. Since for time-dependent problems with a dynamically correct representation of congestion dynamics no better approach is currently known, this is what is done by many groups [5, 4, 6].

From a conceptual point of view, there is no need to use a micro-simulation for the representation of the traffic dynamics. Indeed, traditional assignment models rely on link delay functions, i.e. link travel times depend directly on the demand. It is clear though that this approach becomes dynamically wrong once demand is higher than capacity, and queue spillback spreads through the system [7, 8]. In how far this is important in practice remains an open question. But since metropolitan regions are becoming ever more congested, one should develop and test a methodology that includes a dynamically correct representation of congestion. Monte-Carlo simulations are a common approach to deal with complex systems such as a congested traffic network. Yet, since they often exhibit non-linear behavior, they are unlikely to be treatable analytically.

A large scale approach to this problem is currently pursued by the TRANSIMS project [9]. The next TRANSIMS case study will attempt to simulate the whole city of Portland (1.5 million people) on the level of activities generation, on the level of modal choice and route planning, and on the level of the transportation and traffic dynamics. The main difference to most other projects will be that on *all* levels the approach will model individual people. The advantage of this is that the approach remains conceptually extensible since the behavioral rules of the individuals are directly accessible. The challenge with this approach is computational, since the problem is not only big (1.5 million individuals as said above, and also 200 000 links in the transportation network for a realistic representation), but the relaxation iterations means that the micro-simulation needs to be run many times (up to one hundred times for one relaxation).

TRANSIMS approaches this problem via a combination of fast hardware and a computationally relatively fast traffic simulation approach [10]. Nevertheless, fast hardware is not always

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available, such code is data intensive, and it takes time to write. Mostly for the last reason, TRANSIMS itself uses simplified micro-simulations in order to test the other modules (route planner, activities planner) and in order to test the interactions (feedback) between the modules. Simplified Monte Carlo simulation models for traffic, such as queueing networks [11, 12, 7] or cellular automata [10] are very simple and straigthforward tools to get accurate estimates of traffic flows. Although simulating remains demanding on computers even with simple models, it usually obtains better results than standard approximate methods such as mean-field theory [13] or queueing network approximations [11].

In this paper, we will (Sec. 2) present a simple approach to traffic dynamics in a road network, such as a metropolitan area. The dynamics of the model concentrates on the two arguably most important elements of congestion: capacity cut-offs, and queue spill-back. Capacity cut-offs are modelled by not letting more vehicles leave a link per time slice than is possible according to that link's capacity; and queue spill-back is modelled by a "storage" constraint, i.e. a link can only absorb a limited amount of incoming vehicles. This is followed by a short summary of results for a Dallas scenario (Sec. 3) and by a description of simulation results for Portland (Sec. 4). The paper is concluded by a discussion and a summary.

2 Different models based on queueing theory

2.1 Simao and Powell's queueing model

In 1992, Simao and Powell introduced a simple queueing model based on FIFO (First In First Out) queues [11]. In this model, each node is represented by one unloading queue and as many departing queues as there are departing links. When a customer arrives at a node, he is automatically transferred to the unloading queue. A sorting step takes place to position each customer on the departure queue i with probability p_i, or out of the system with probablity $1 - \sum p_i$. In the departure queue, the customer can leave or be hold depending on the service rate for this queue.

Links are divided into sub-links. Vehicles move forward from one sublink to the next at every time step. The travel time between two consecutive nodes is therefore deterministic. It is interesting to notice the similarity with cellular-automata (CA) based simulations which decompose links into a series of fixed-length boxes.

The simplicity and the main purpose of the queueing model by Simao and Powell is to allow some analytical investigations. Simao and Powell showed that in some simple cases the approximation method is more appropriate; but it fails for general conditions.

The main question about this model is if it contains the minimal description necessary to reproduce microscopic traffic characteristics. In fact, the introduction of an unloading queue with infinite storage does not allow the creation of spill backs, so typical of a crowded network. Spill backs are caused by links that become full, which happens when demand is higher than capacity, i.e. more vehicles enter the link than can leave. Full links do not accept any further vehicles, thus clogging up links which contain vehicles that want to enter the full link. In this way, a single link where demand exceeds capacity can cause congestion to spread through a network.

2.2 Gawron's model

In 1997, Gawron introduced a model similar to Simao and Powell's model in its architecture [12, 7]. The main difference to the previous model resides in the modelling of spill-backs. The number of vehicles leaving a link is constrained by the capacity of the link, *and* by the number of cars which can fit on the destination links. If its destination link is full, a vehicle will stay where it already is.

Each time a car enters a link, an expected travel time is calculated. An early version of this model proposed to calculate this travel time from the length and the current state of the link. A fundamental diagram proposes a desired velocity according to the current density [12]. A newer version only assumes to consider the free flow velocity to calculate the travel time [7]. We will use the same simulator in this paper and present new results on the Portland network.

2.3 Fundamental diagram

One of the most important feature of the queueing model is to produce reasonable travel times in the laminar and congested regimes. A fundamental diagram can be extrapolated from the parameters of the model itself. Let us consider a queue with free flow velocity v_0 in (m/s). We call L the length of the link, C its capacity (*vehicles/second*) and n_{lanes} the number of lanes of the link. The maximum number of vehicles that can be added to the link is $N_{sites} = L \cdot n_{lanes} / \ell_{site}$ where we set the space taken by one vehicle in a jam to the inverse of the jam density: $\ell_{site} = 1/\rho_{jam}$. For this paper, l_{site} is set to 7.5 meters. The number of sites of the link, N_{sites}, is also the maximum number of vehicles in the queue. Free flow travel time is given by the relation $T_0 = L/v_0$.

For illustration, let us now put n vehicles in the queue at time t and suppose that when a vehicle is allowed to leave the link, it is automatically put at the end of the same queue ("traffic in a loop with one stop light"). We therefore keep the density constant and define different regimes according to the density. There are three regimes:

- **Laminar regime.** In the laminar regime, demand is smaller than capacity. In the queueing model case, it basically means that nobody spends more than T_0 seconds on the link. The average velocity is simply given by v_0.

- **Capacity regime.** As soon as the build-up of the queue is longer than what the capacity of the link can dissolve in T_0 seconds, we can consider the queue in the congested regime. In our closed system, this simply means that the first vehicle released from the queue after the start of the simulation will be ready to leave again (according to T_0) before the vehicle in front of it has left. The critical density for which vehicles begin to wait longer than T_0 is given by

$$\rho_1 = \frac{C \cdot T_0}{N_{sites}} \ .$$

When the density ρ is higher than ρ_{c1}, the expression of the travel time can be given by $t = t_0 + (n - C \cdot t_0)/C = n/C$, which simply means that one can leave the link once all n vehicles in front have left the link, and this takes a time of n/C.

This leads to the expression for the velocity:

$$v = \ell_{site} \frac{C}{n_{lanes}} \frac{1}{\rho} = \frac{K}{\rho}$$

where $K = \frac{\ell_{site} \times C}{n_{lanes}}$. The velocity in the capacity regime is thus a product of a model parameter (ℓ_{site}), a link parameter (C/n_{lanes}), and the inverse of the density.

- **Jammed regime.** The velocity goes towards zero when the queue is almost full and vehicles have difficulties to leave the queue because there is no space available. For this, it is easier to imagine that the closed loop is composed of two links. During one time step, the first link is picked. Vehicles leave until all empty spaces in the second link are filled up, and vehicles are moved forward on the first link. Then, the same happens for the second link. Clearly, the number of vehicles $n(t)$ that leave the link by time step is the same as the number of empty sites, $n_{empty}(t)$. Since $n(t)$ is the same as the flow, and density $\rho(t) = (N_{sites} - n_{empty}(t))/N_{sites}$, one obtains $\rho = (N_{sites} - q)/N_{sites}$. The link is in this regime for

$$\rho \geq \rho_2 = 1 - C/N_{sites} .$$

A typical fundamental diagram would look like Fig. 1. Velocities in the queueing model do not go "smoothly" to zero for $\rho \to 1$; instead, they have a "kink" at $\rho = 1 - C/N_{sites}$. The velocity here is $K \cdot L/(L - K)$. This means that if the link is long enough, this value is close to K, which depending of the characteristics of the link, is not necessarily close to zero.

The physical reason for this is that "holes" can travel in one time step from the beginning of the link to the end in the queue model. This is opposed to real traffic, where, say, a light turns green, then the first car moves and opens up space for the second, then the second car moves and opens up space for the third, and it takes quite some time until this effect has travelled up a link.

The consequence of this behavior for traffic simulation purposes is that simulated traffic will be more "fluid" in the very congested regime than when using a model where speed goes "smoothly" to zero for $\rho \to 1$. Having somewhat fluid traffic in the very congested regime is though not necessarily a disadvantage since, in a network context, current similation-models seem to grid-lock more easily than reality [14, 15].

2.4 Algorithm of the queueing model

The description in the last section should be sufficient to obtain a model similar to ours. Nevertheless, in this section we want to give a more precise description of the algorithm that we used. We call C_{link} the capacity of a link in vehicles/second. N_{link} is the number of vehicles which already left the link during the same time step, and *rand* is a random number between 0 and 1. We denote $\lfloor x \rfloor$ the floor of x.

- For all links DO:

    - WHILE ($N_{link} < \lfloor C_{link} \rfloor$ OR ($N_{link} = \lfloor C_{link} \rfloor$ AND $rand < C_{link} - \lfloor C_{link} \rfloor$)) DO
        * Look at the first vehicle in the queue.

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* If the free speed arrival time is larger than the current time, then break and go to the next link.
* Check if the destination link has space. If not, break and go to the next link.
* Calculate the expected arrival time on the end of the next link:
  Arrival time = Current time + length/freespeed
  (length and freespeed of the destination link)
* If passing is allowed, insert vehicle into the destination queue sorted by time
* If passing is not allowed, insert vehicle at the end of the destination queue

ENDDO

ENDDO

Passings allow the model to handle vechicles with different maximum velocities, for example cars and buses. In this case, priority queues are necessary.

Note that the simulation runs on pre-computed route plans, as explained below. Such a simulation can become "stuck" or grid-locked, for example when a loop of full links forms, and the first car on each of these links wants to move into another of these full links [14, 15]. In order to prevent this, we remove vehicles that are first in a queue and have not moved for T_{wait} time steps of the simulation. For the simulations in this paper, we used $T_{wait} = 300$ seconds (= 300 simulation time steps). In the iterative procedure (explained later), many such vehicles were removed in the first iterations, but their number is less than 0.5% in the 40th iteration (Fig. 2 c).

3   Previous results on a Dallas case study

We compared the queue model (QM) with two other, more realistic micro-simulations in the context of the TRANSIMS Dallas–Fort Worth case study [16]. Comparisons of link densities and of accessibility can be found in [17], comparisons of turn counts (also with field data) can be found in [18]. For these studies, all three simulations used the same trip table (origin–destination matrix), and they used the same router for iterations between simulation and re-routing. The major result of these comparisons was that the results of all three simulations were remarkably similar, indicating that deviations from reality are currently most probably to a larger extent caused by the travel demand generation algorithms and by the routing algorithm than by the micro-simulations.

4   Simulation results on Portland

In this paper, we want to concentrate on results for Portland (Oregon), which is the study area for the next TRANSIMS case study.

4.1   Activities and iterative replanning

TRANSIMS [9], in its full design, uses data on demographics and in transportation infrastructure as input. The following steps are then performed:

- **Synthetic population disaggregation:** As the first step, it generates a synthetic population from the demographic data [19], that is, TRANSIMS looks at synthetic individuals and their decision-making process rather than at the behavior of aggregated quantities. The synthetic individuals possess many relevant attributes such as the number of persons living in the same household or the number of cars per family.

- **Activities generation:** Travel demand is generated via activity patterns and activity locations. This synthetic population is then combined with the land use data to produce activity assignements. This basically tells us where a person works and what her other schedules are.

- **Modal and route choice:** A modal choice and routing module generates explicit "travel plans" for each synthetic individual.

- **Travel:** The micro-simulation (such as the QM model presented in this paper, or more realistic micro-simulations) executes all travellers' plans simultaneously and thus computes the nature of the interactions between travellers, especially congestion.

It is well-known that the above steps cannot be performed uni-directionally because backward causalities exist. For example, congestion will make people change their mode of transportation and/or their routes. If that does not help enough, they may change their activity locations and/or their activity schedule.

TRANSIMS (and several other projects [5, 4, 6]) approach this problem via *feedback*, i.e. iterations between the modules. Initial activities and travel plans are generated, the micro-simulation runs based on these plans, some synthetic travellers change modes and/or routes, the micro-simulation is run again, etc., until some stopping criterion is fulfilled.

For the Dallas case study, the activities generation module was not yet in place. Thus, the Dallas case study used conventional trip tables as starting point and essentially performed an assignment of the trip table on the network, except that the trip tables were explicitely time-dependent, the assignment was performed on the level of individual drivers, and the dynamics of congestion and queue spill-back (and much more) was explicitly and realistically represented.

The activities used for *this* paper were a simple home-to-work assignment. This is not done with the intention of being as realistic as possible but with the intention of understanding the dynamics of the computational process by using a simplified partial problem. The input data here is (i) a list of all synthetic individuals in the simulation who work, and (ii) a list of all workplaces. Workers and workplaces are assigned by using a distance-based preference function [20]. This activity set leads to approximately 500 000 trips, all between 4am and 10am.

Routing is done using time-dependent fastest path. Link travel times are given in 15-minute aggregates from the last iteration of the microsimulation. For the initial route plan set, free speeds on the links are used. Travellers only have cars available; the integration of other modes is currently being done but not yet operational. For route re-planning, we only change routes for a fraction of the population. This fraction is approximately 5%, and selection is done with a heavy bias towards individuals who have not re-planned their route for a large number of iterations ("age-dependent re-planning", [21]). By iterating this process, we reach a relaxed state, where no more changes are observed from one iteration to the next, except from random fluctuations. For morning peak simulations, this typically takes 20 to 40 iterations, see Fig. 2.

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The network that we used was the same that the Portland MPO ("Portland Metro") uses for their emme/2 runs. The important information for our model were: length of links, capacity of links, free speeds or speedlimits, and storage capacity for full link (computed via length and number of lanes). Except for the storage capacity, this is the same information that is used for traditional assignment. The network has 20,024 uni-directional links and 8,564 nodes.

We simulated traffic between 4am and noon; in order to simulate these 8 hours with half a million trips on the above network, we needed about 17 minutes on a 250 MHz SUN UltraSparc CPU. Computational speed on a Pentium CPU should be about the same or faster.

4.2   emme/2 results

For comparison, we use results from a Portland emme/2 AM peak assignment (Fig. 3). These results were provided by the Portland MPO (Portland Metro) and were run on the same network that we were using. Yet, we are not using the same origin-destination table as the emme/2 assignments since we are generating transportation demand via activities as described above. For that reason, the results are not strictly comparable and the emme/2 results should be considered as a baseline only.

Note that even if we were using the same demand table as emme/2, this would not help much because in the end we want to match reality, not some other model. In consequence, a truly useful comparison study with traditional assignment would need field data (such as turn counts), and one would also have to compare the traditional way of demand generation with the activity-based demand generation, both for the traditional assignment and for the simulation-based assignment. Although such a study would certainly be useful, it is outside the scope of the current TRANSIMS project.

4.3   Queue model simulation results

Fig. 4 shows results of our microsimulation-based assignment using the simplified home-to-work activities. As mentioned earlier, the simulations run on the same network as the emme/2 assignment except that some additional information is needed in order to get the storage capacity of the links. We show results of the 40th iteration of the feedback process.

The plots show average hourly speeds on all links according to the legend; red links have low speed, probably caused by congestion. Underneath, links are marked in light gray, with the width corresponding to their capacity, in order to identify high-capacity links. Since our method is explicitly time-dependent, we show plots for the periods 6-7am and 7-8am.

Clearly, even after many iterations, there remains a significant number of bottlenecks that prevent traffic from going to their destinations. Contrary to traditional assignment, the simulations cannot "push" demand through bottlenecks at a rate higher than capacity, so that traffic jams up and spills back.

Fig. 5 shows comparisons to the emme/2 assignment for the different hourly periods. The shown volumes are hourly volumes; for example, Fig. 5 b corresponds to the volume between 7am and 8am. This is also the time slot where the dynamics is probably closest to the emme/2 assignment.

In the 6-7am time slot (Fig. 5 a) we have much more traffic *out* of the city than the emme/2 assignment. This is probably a result of the overly simplistic assumptions of the workplace

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assignment (which is homogeneous in space).

In the 7-8am period (Fig. 5 b), there are two dominant features when compared to the emme/2 assignment: (i) we have much more traffic northbound across the bridges. This comes out of assigning too many workplaces in Washington to workers living in Oregon, see [20]. Better sets of workplace assignments should correct this. (ii) We have significantly *less* flow on I-84 westbound, which is the somewhat zigzagging green line extending east from downtown. Further inspection yields that this is *not* the result of not enough traffic but rather of too much traffic, which jams up when it tries to reach the bridges across the Williamette River and then spills back into the interstate. Similar effects, although to a lesser extent, can be found on some other of the freeways, especially where they merge and upstream from there. This effect is not necessarily unrealistic since it is a consequence of the most important dynamic difference between traditional assignment and simulation-based assignment, although it seems to be a bit too strong on I-84. Field data (planned for Portland) would be necessary to clarify this issue.

5 Discussion

As usual, we are left with the unsatisfactory feeling that we now know some differences between the approaches, but we still do not know which approach is better at what aspects of reality. Although Portland Metro is working on it, there is currently no field data for comparison purposes available. Even when it becomes available, this will not be the solution to all problems because differences to data can be caused by the activities generator, the router, the micro-simulation, or even by network changes (for example, Portland closed the Hawthorne Bridge across the Williamette river for a year for maintenance). As mentioned further above, a comprehensive comparison study would certainly be useful. This study would have to include systematic evaluations of the demand generation, to circumvent the problem that current origin-destination matrixes may be adjusted to work well with the emme/2 technology (and may thus work less well with the simulation-based assignment). And it seems a bit too early for such a study since the microsimulation-based technique is not yet well enough understood on its own.

Yet, the fact that we can run the complete microscopic dynamic assignment of half a million trips on a 20 000 link network in less than half a day on a single workstation CPU is an astounding feat in itself. Clearly, technology has enabled us to make a big jump in what is feasible, and much work remains to be done to make these opportunities useful for transportation planning.

6 Conclusion

We presented a simplified traffic micro-simulation. This micro-simulation is consistent with a microscopic approach to demand generation, that is, it operates on individual route plans. The approach is based on the simulation of queues, where vehicles can leave a queue only if capacity restrictions allow it and if there is space on the destination link. In addition, a vehicle needs to spend at least the free speed travel time on a link. This achieves that situations where demand is larger than capacity automatically lead to queue formation, and because of limited "storage" capacity on the link, the jam will eventually spill back through the network. The model essentially needs emme/2 type network data as input, plus the number of lanes to compute the storage capacity.

We showed a first application of this model for Portland. The emme/2 network that Portland Metro uses has 20 000 links; we ran about half a million home-to-work trips through this network. Feedback iterations were used to relax the routes; results of the final iteration were shown and compared to emme/2 results. Because of lack of field data, no final conclusions can currently be drawn. Yet, the fact that such studies can be done on a single workstation CPU in less than half a day of computing timeis an enormous technological achievement, and exploratory studies such as the one described in this paper are necessary to understand this new technology better and to obtain a broad technology base in the area.

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Figure 1: Fundamental diagrams flow vs. density and velocity vs. density for the Q-model when run in a closed loop.

Figure 2: Different indicators of routing relaxation. (a) Sum of all travel times vs. iteration number. (b) Number of vehicles in the simulation as function of the time-of-day. Different curves for different iteration numbers. (c) Number of removed cars. As explained in the text, cars that are first in the queue but do not move for T_{wait} time steps because their destination link is full are removed from the simulation.

Figure 3: Result of the emme/2 assignment. The width of the light gray denotes capacity. Green, red, and dark red colors mark links with "emme/2 volume"-to-capacity ratios 0.5–1, 1–1.2, and > 1.2, respectively.

Figure 4: Result of our own route assignment using simplified home-to-work trips, and feedback iteration between a fastest path re-planner and the queue model (QM) micro-simulation. The width of the light gray denotes again capacity. The colors denote average hourly speeds, as indicated in the legend. (a) Averaged from 6 to 7 am; (b) Averaged from 7 to 8 am.

Figure 5: Using the same simulation results as in Fig. 4 and comparing them to the emme/2 assignment. The width of the light gray denotes again capacity. The colors show differences between our simulation results and the emme/2 assignment flow results; red means that we have more flow, green means that we have less flow. (a) Averaged from 6 to 7 am; (b) Averaged from 7 to 8 am.
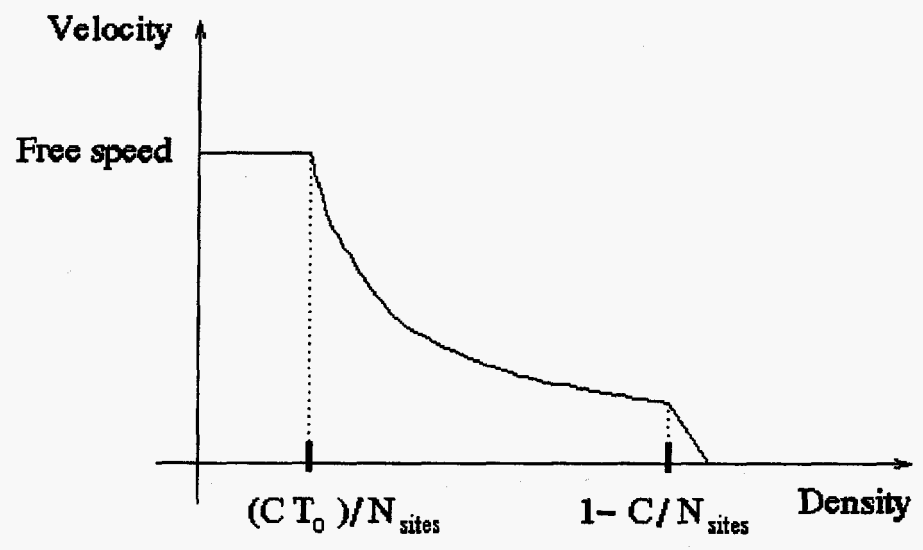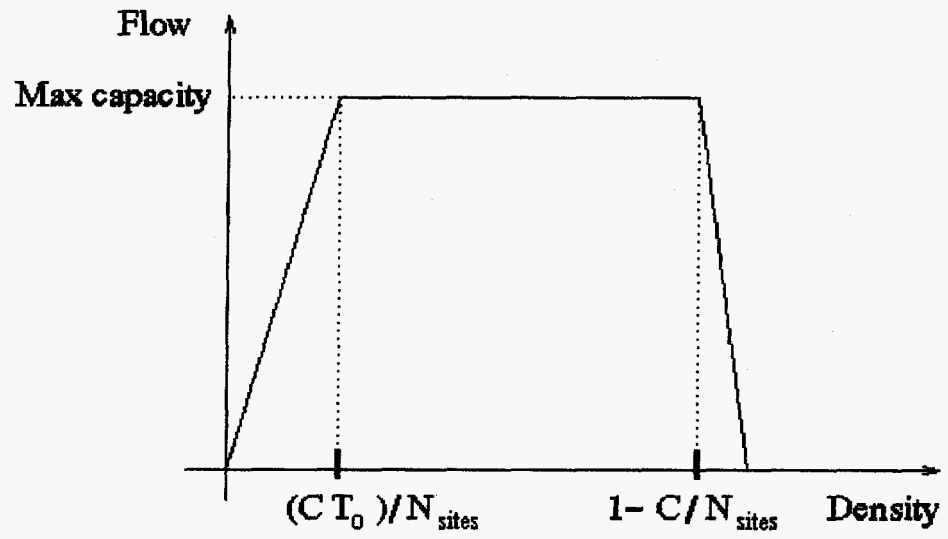
Fig. 1
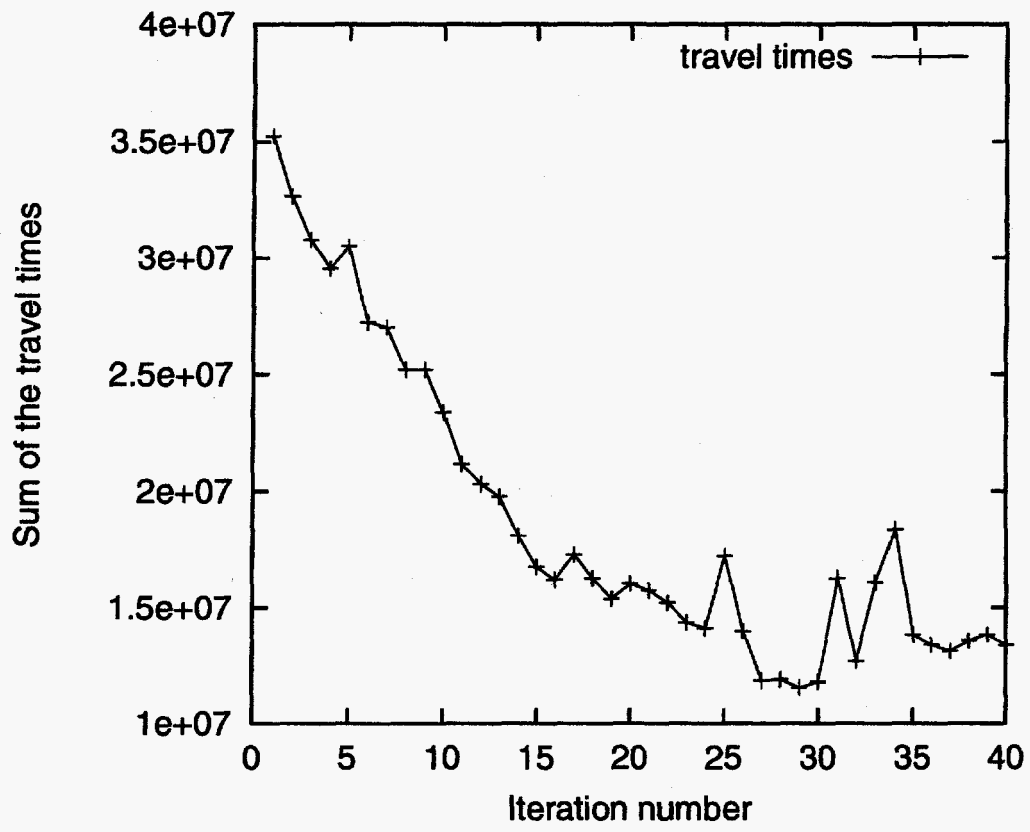
Fig. 2 a
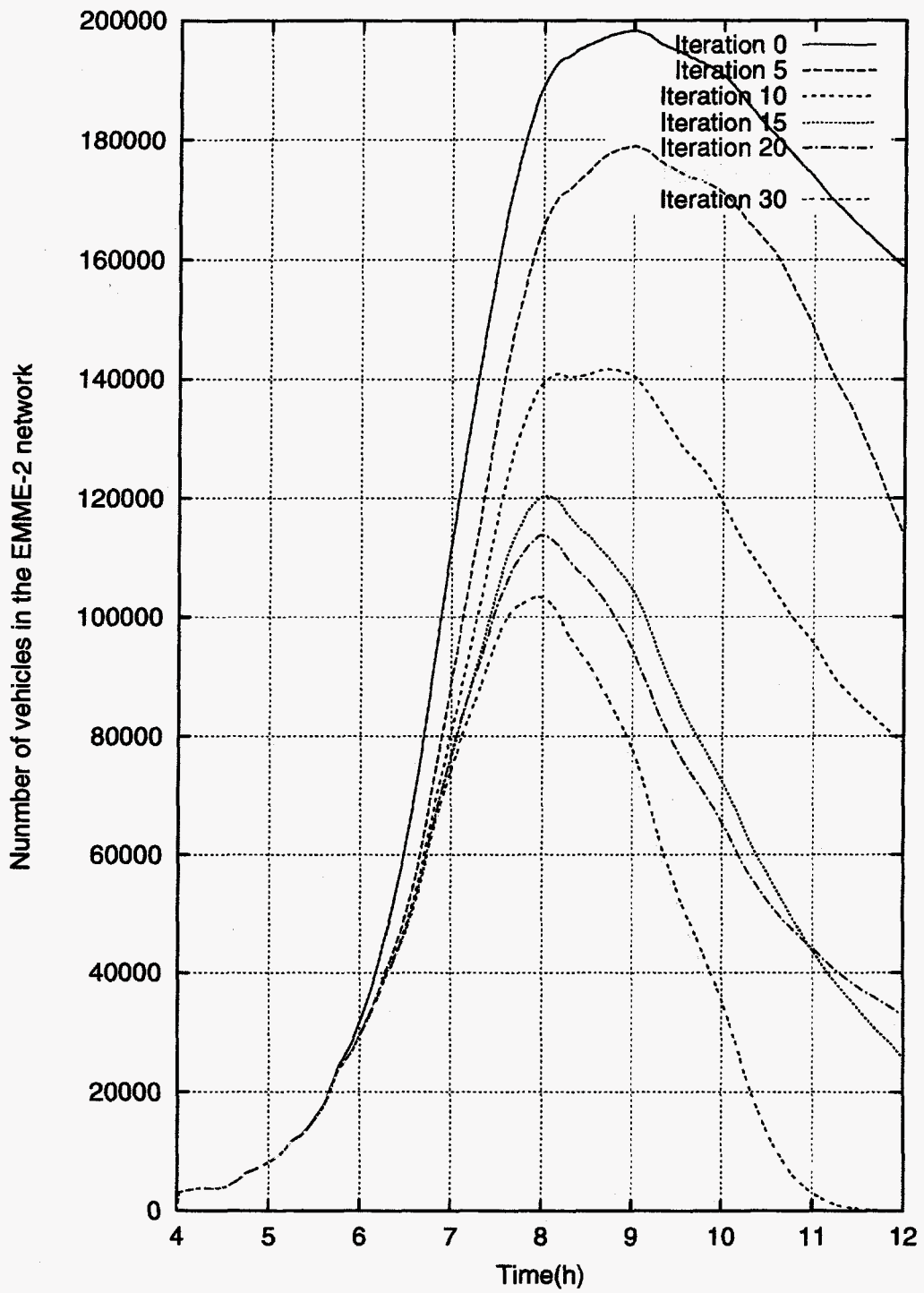
Fig. 2 b
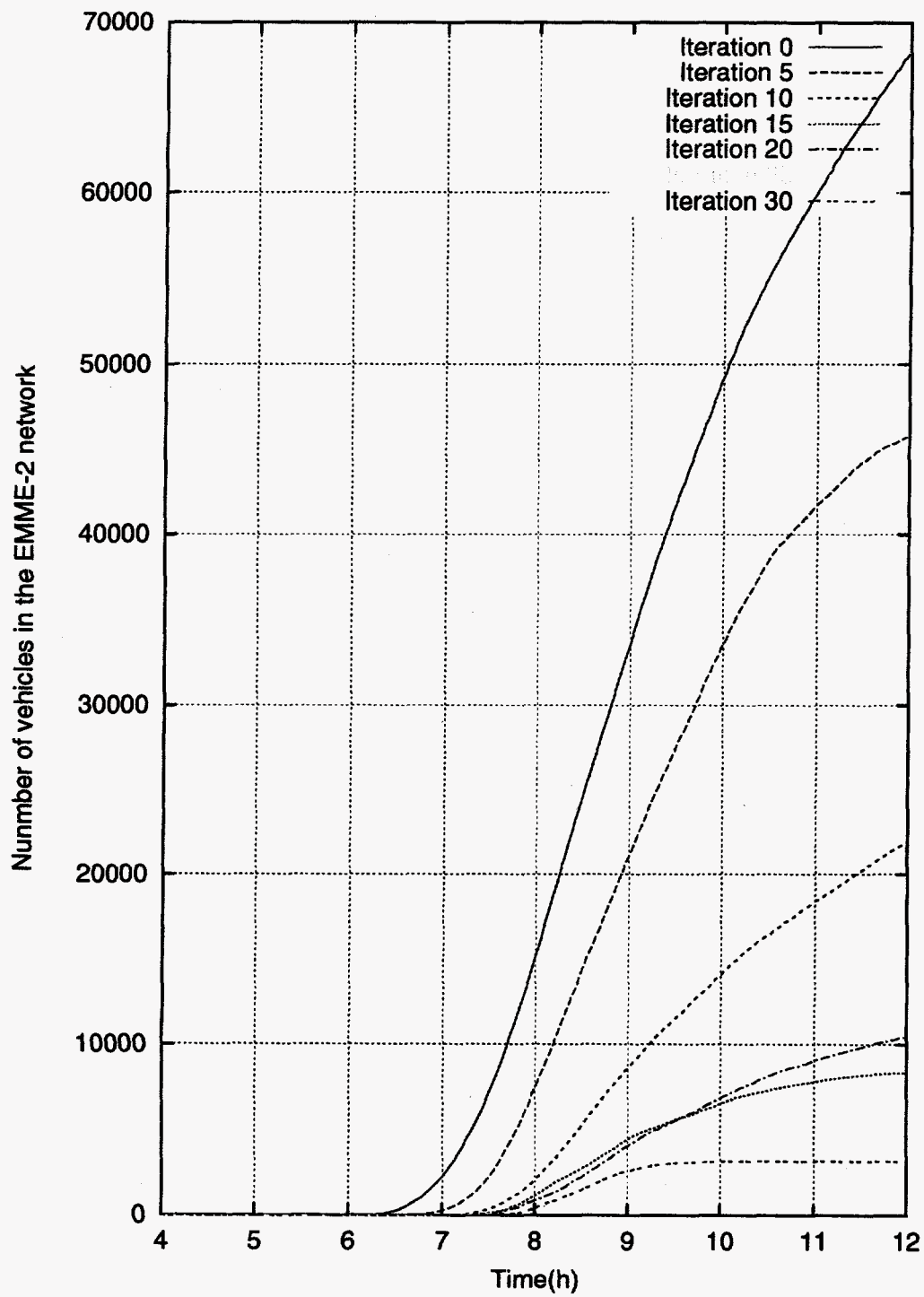
Fig. 2 c

Emme/2 Assignment

(Emme/2 Volume)/Capacity
   0 - 0.5
   0.5 - 1
   1 - 1.2
   >1.2
Capacity (veh/h)
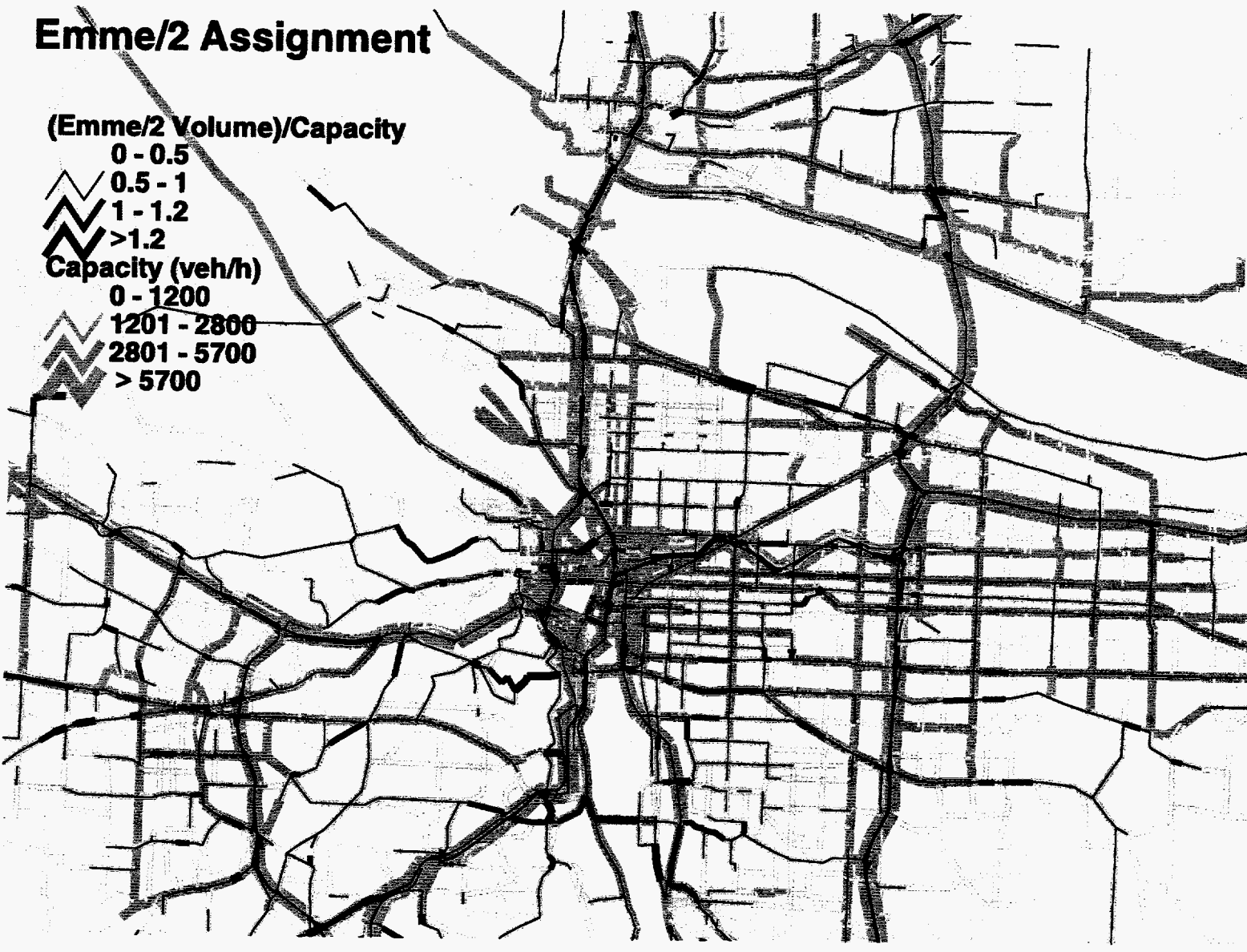   0 - 1200
   1201 - 2800
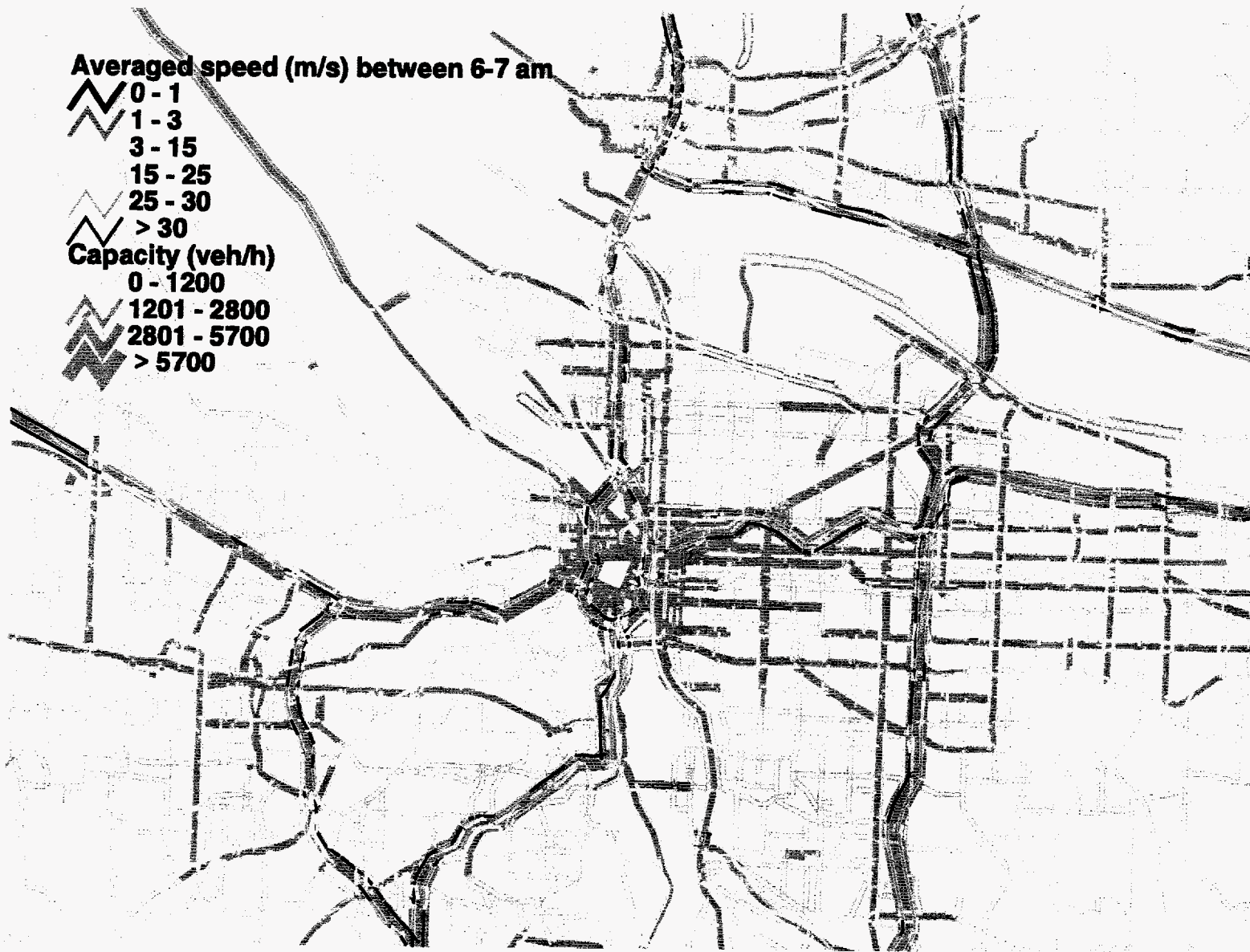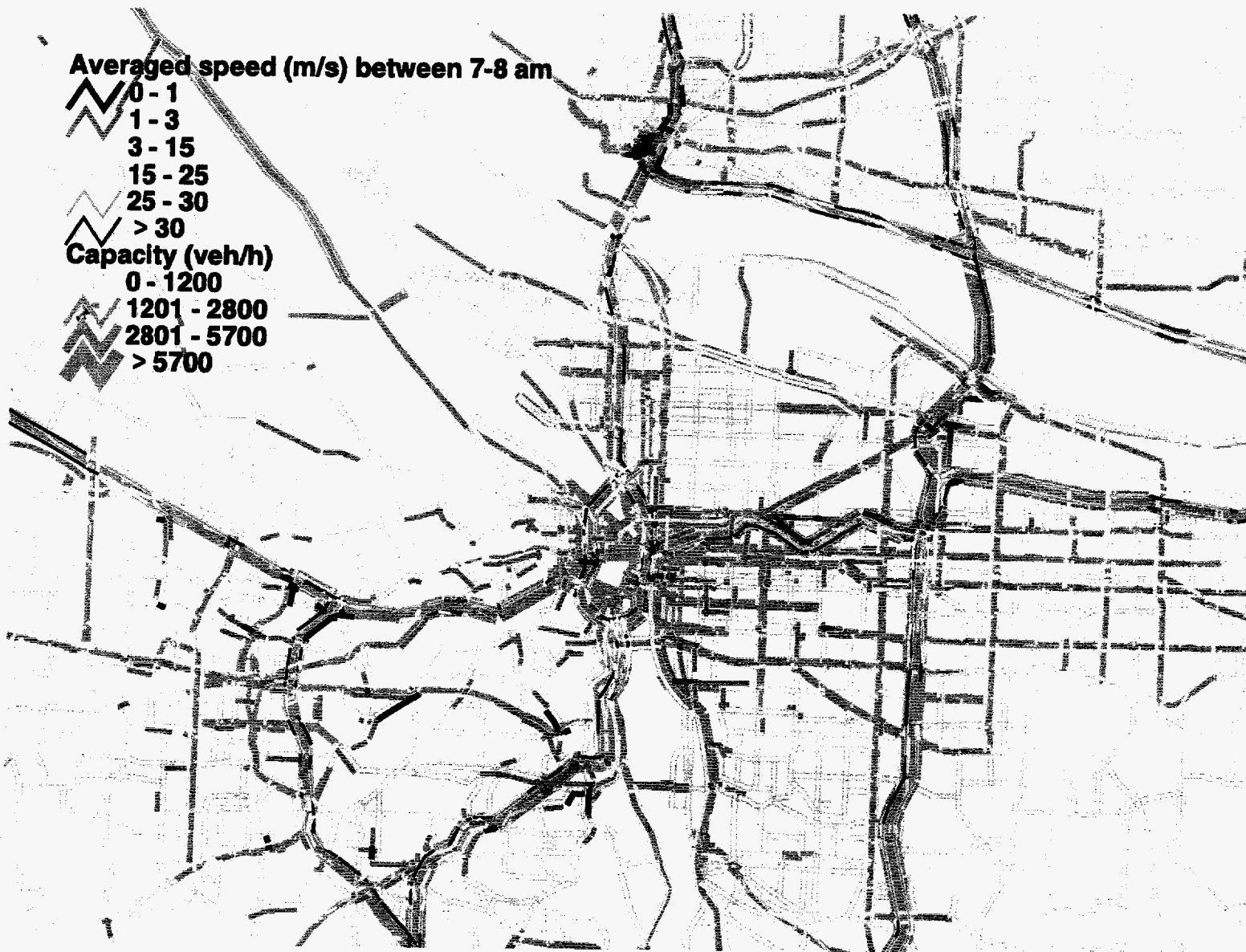   2801 - 5700
   > 5700

Fig. 3

Averaged speed (m/s) between 6-7 am
0 - 1
1 - 3
3 - 15
15 - 25
25 - 30
> 30
Capacity (veh/h)
0 - 1200
1201 - 2800
2801 - 5700
> 5700

Fig. 4 a

Averaged speed (m/s) between 7-8 am

- 0 - 1
- 1 - 3
- 3 - 15
- 15 - 25
- 25 - 30
- > 30

Capacity (veh/h)

- 0 - 1200
- 1201 - 2800
- 2801 - 5700
- > 5700

Fig. 4 b

Av (QM vol - Emme/2 Vol) between 6-7 am
- -6029 - -3771
- -3770 - -1513
- -1512 - 745
- 746 - 3003
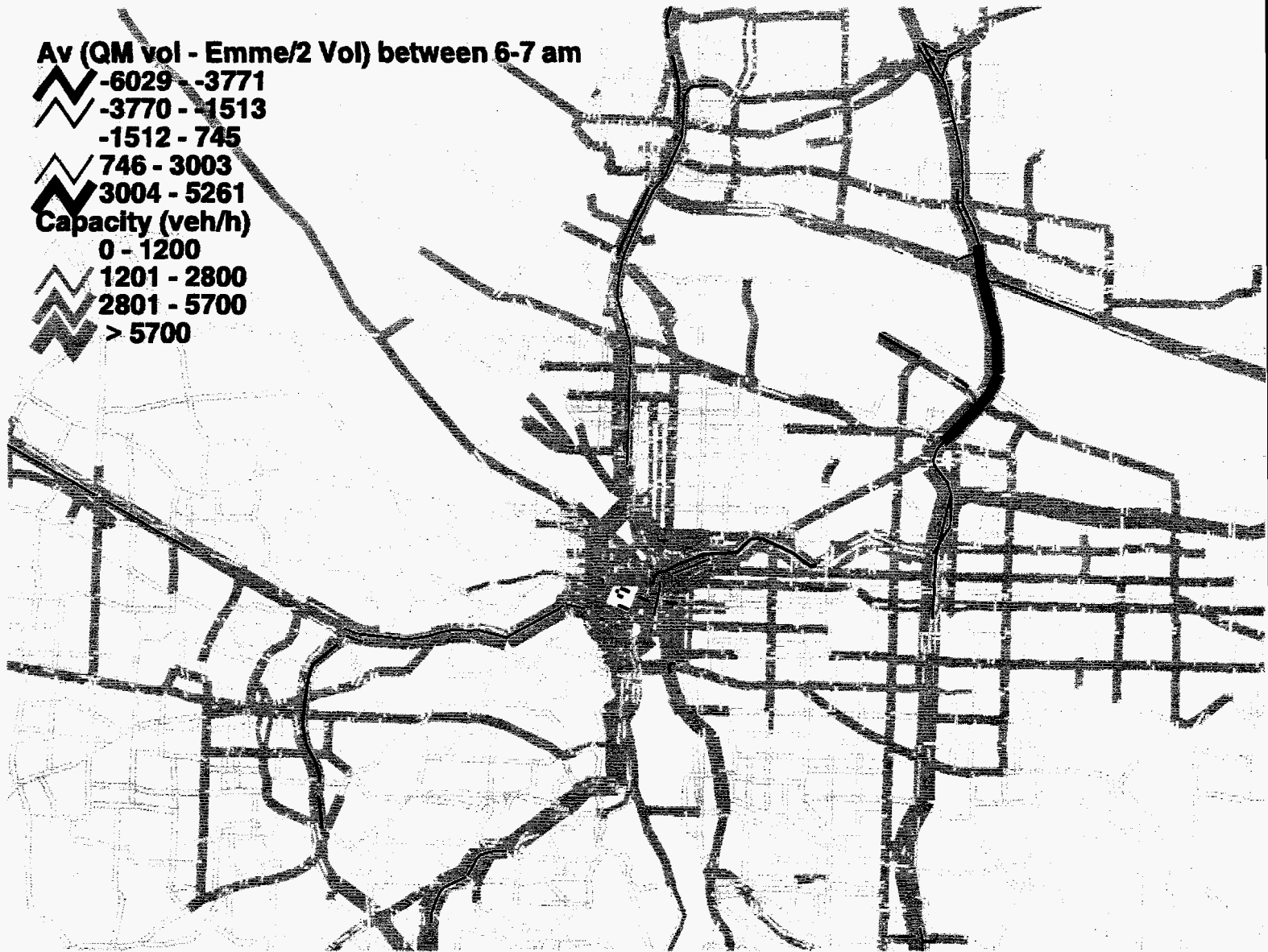- 3004 - 5261

Capacity (veh/h)
- 0 - 1200
- 1201 - 2800
- 2801 - 5700
- > 5700

Fig. 5 a

Av (QM vol - Emme/2 Vol) between 7-8 am
- -6029 - -3771
- -3770 - -1513
- -1512 - 745
- 746 - 3003
- 3004 - 5261

Capacity (veh/h)
- 0 - 1200
- 1201 - 2800
- 2801 - 5700
- > 5700

Fig. 5 b