# A Model of the Rise and Fall of Roads

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## Abstract

Transportation network planning decisions made at one point of time can have profound impacts in the future. However, transportation networks are usually assumed to be static in models of land use. A better understanding of the natural growth pattern of roads will provide valuable guidance to planners who try to shape the future network. This paper analyzes the relationships between network supply and travel demand, and describes a road development and degeneration mechanism microscopically at the link level. A simulation model of transportation network dynamics is developed, involving iterative evolution of travel demand patterns, network revenue policies, cost estimation, and investment rules. The model is applied to a real-world congesting network – the Twin Cities transportation network which comprises nearly 8,000 nodes and more than 20,000 links, using network data collected since year 1978. Four experiments are carried out with different initial conditions and constraints, the results from which allow us to explore model properties such as computational feasibility, qualitative implications, potential calibration procedures, and predictive value. The hypothesis that road hierarchies are emergent properties of transportation networks is confirmed, and the underlying reasons discovered. Spatial distribution of capacity, traffic flow, and congestion in the transportation network is tracked over time. Potential improvements to the model in particular and future research directions in transportation network dynamics in general are also discussed.

Keywords: Transportation network dynamics, Urban planning, Road supply

# 1. Introduction

In 1900 there were 240 km of paved road in the United States (Peat 2002), and this total had increased to 6,400,000 by 2000 (BTS 2002) with virtually 100% of the U.S. population having almost immediate access to paved roadways. The growth (and decline) of transportation networks obviously affects the social and economic activities that a region can support, yet the dynamics of how such growth occurs is one of the least understood areas in transportation, geography, and regional science. This lack of understanding is revealed time and again in the long-range planning efforts of metropolitan planning organizations (MPOs), where transportation network change is treated exclusively as the result of top-down decision-making. Non-immediate and non-local effects are generally ignored in planning practices because the complete network effects are incomprehensible with the current tools, which often results in myopic network expansion decisions. If one looks at the complexity and bureaucracy involved in transportation infrastructure investment, one might conclude that it is impossible to model the transportation network dynamics endogenously. However, changes to the transportation network are rather the result of numerous small decisions (and some large ones) by property owners, firms, developers, towns, cities, counties, state department of transportation districts, MPOs, and states in response to market conditions and policy initiatives. Though institutions make network growth (decline) happen on the surface, network dynamics are indeed driven by some underlying natural market forces and hence predictable. Understanding how markets and policies translate into facilities on the ground is essential for both scientific understanding and improving forecasting, planning, policy-making, and evaluation.

A transportation network is a complex system that exhibits the properties of self-organization and emergence. Previous research in dynamics related to transportation networks focuses on traffic assignment or traffic management. However, the dynamics of transportation network growth have not been adequately studied. If a transportation network is represented by a directed graph, there are several important questions yet to be answered: (1) How do the existing links (roads) develop and degenerate? (2) How are new links added to the existing network? (3) How are new nodes added to the existing network? This paper concentrates on the first question and focuses only on the rise and fall of existing roads, recognizing the inter-dependence of road supply and travel demand. The approach is microscopic in that network dynamics are modeled at the link level. The following key questions are examined:

(1) Why do links expand and contract?

(2) Do networks self-organize into hierarchies?

(3) Are roads (routes) an emergent property of networks?

(4) What are the parameters to be calibrated in a microscopic network dynamics model?

(5) Is the model computationally feasible on a realistic transportation network?

(6) Is the model capable of replicating real-world network dynamics?

One of the few previous studies (Yerra and Levinson 2002) in this area shows that even starting from a random or an uniform pattern, a transportation network tends to self-organize into a hierarchical pattern in which some roads attract more traffic, receive proper maintenance, and are gradually expanded, while some other roads are less popular, poorly maintained, and may eventually be abandoned. It is also demonstrated that although these hierarchies seem to be designed by planners and engineers, they are actually intrinsic emergent properties of networks themselves. However, the simulation model developed in that study is restricted in several ways. First, the links are assumed to have unlimited capacities. The impacts of network congestion on travel demand are ignored. The assumption also results in another unrealistic property of the model - the growth and decline of links are only reflected by changes of their free-flow speeds. Secondly, their model is tested only on simple hypothetical networks and it is not clear if the conclusions regarding road hierarchies hold on large-scale realistic networks. Those two restrictions are relaxed in this study. Travel demand is represented by a more realistic user equilibrium pattern. In the network evolution process, links exhibit dynamics in both free-flow speed and capacity. The improved model is then applied to the Twin Cities transportation network with nearly 8,000 nodes and more than 20,000 links, which allows us to examine computational properties and predictive value of the proposed microscopic network dynamics model.

The next section presents a brief review of related literature in regional science and economics. Though the reviewed studies have dissimilar objectives and methodologies, they all shed some lights on the nature of transportation network growth and its social-economical impacts. The following section develops a theoretical framework for studying the rise and fall of roads. The framework helps identify various influencing factors and inter-dependences among those factors, based on which a synthesis model of road expansion and contraction is developed in Section 4. The model is applied to the Twin Cities transportation network from year 1978 to 1998 with different model parameters and starting conditions. The results of those experiments are summarized, and the listed research questions answered in Section 5. Conclusions and future research directions are offered at the end of the paper.

## 2. THEORETICAL BACKGROUND

Few researchers have considered the process of transportation network growth at microscopic level, highlighting the importance of this research. Taaffe et al. (1963) study the economic, political and social forces behind infrastructure expansion in underdeveloped countries. Their study finds that initial roads are developed to connect regions of economic activity and lateral roads are built around these initial roads. A positive feedback between infrastructure supply and population was also observed. Barker and Robbins (1975) investigated the London Underground's growth, but did not develop a theoretical framework as we are considering here. Miyao (1981) developed macroscopic models to take transportation improvements as either an endogenous effect of urban economy or as an exogenous effect on the economy. Endogenous growth theory suggests that economic growth is a two-way interaction between the economy and technology; technological research transforms the economy that finances it (Aghion and Howitt 1998). The technology of transportation is unlikely to be an exception, suggesting transportation investment drives the growth that funds it. Macroscopically, the growth of infrastructure follows a logistic curve and that road infrastructure also has reached saturation levels in developed countries (Grübler 1990). Miyagi (1998) proposes a Spatial Computable General Equilibrium (SCGE) model interacting with a transportation model to study the interaction of transportation and the economy. Yamins et al. (2003) develop a road growth model to study co-evolution of urban settlements and road systems from an empty space with highly simplified travel demand and road supply mechanisms meaningful only for theoretical works.

Carruthers and Ulfarsson (2001) find that various public service expenditures like roadways are influenced by demographic and political characteristics. The New Jersey Office of State Planning (1996) also finds a similar pattern in roadways expenditure. A related line of research examines how transportation investment affects the economy at large, but tends to treat transportation (or highways) as a black box, and makes no distinctions between different kinds of transportation investment (Aschauer 1989, Boarnet 1997, Button 1998, Gramlich 1994, Nadiri and Mamuneas 1996). The input is investment in transportation (or infrastructure), and output is gross domestic product, measured at the state level. While this research provides no assistance in actually making management decisions, it suggests a way that a macroscopic network investment budget can be established.

Geography's central place theory seeks to explain how hierarchies of places develop (Christaller 1966). Models developed by Batty and Longley (1985), Krugman (1996), and Waddell (2001) consider land use dynamics, allowing central places to emerge. However, those models take the network as given. Clearly, there is a need for research that makes the network the object of study. In many respects, the hierarchy of roads is the network analogue of the central place theory.

## 3. NETWORK DYNAMICS AT THE MICROSCOPIC LEVEL

Regional economic growth is taken as exogenous for this study of transportation network dynamics because transportation infrastructure is not the only factor that drives economic growth and we do not yet have adequate other models to explain change in land use. It has long been known that transportation service and land use influence each other though iterative changes in accessibility and travel demand. However, land use dynamics are also treated as exogenous in the following network analysis, so that attention can be focused on transportation network growth, a process with enough complicated and unknown dynamics for one to start with. This limitation can be removed in future research. The dynamics of other factors involved such as travel behavior, link maintenance and expansion costs, network revenue, investment rules, link expansion and degeneration, are considered endogenously.

The foremost and probably also the most important constraint on future network growth is the existing network. In developed countries where transportation infrastructure has reached its saturated stage, it is rare to see new network growth from a *tabula rasa*. Even in an empty place without any previous developments, natural barriers such as rivers and mountains still impose constraints on future network growth. The current network connectivity determines whether two links complement (upstream or downstream) or compete (parallel) each other for demand. The existing network may or may not be at an equilibrium. It may still take years for road supply to meet existing travel demand even if no exogenous changes (e.g. population and economic growth) occur. The important question is how various forces drive the existing network to evolve, more than how long it takes.

Based on the current network, land use arrangements and individual socio-economical status, people make their travel decisions such as trip frequency, scheduling, destination, mode and route choices. These decisions transform into travel demand on the transportation network. This demand-generating process involves the existing network supply, congestion externalities, travel behavior, and link-level travel demand forecasting.

Transportation is a service and travelers pay to obtain that service in addition to spending their own travel times. In the US that payment is largely in the form of a fuel tax. However, if links were autonomous, they would set prices to maximize their profits in the form of a vehicle toll. In many real-world transportation networks, government agencies collect transportation revenue in terms of fuel taxes. We can set the price for using a link as a function of the length and the level of service (LOS) of the link. It is convenient to use a notion of link revenue. Revenues collected by individual links may or may not be pooled together for investment purposes depending on the underlying institutional structure of the network. Longer, faster, and high-demand (traffic flow) links should be able to generate more revenues. If not maintained appropriately, link LOS will decrease over time due to physical deterioration caused by the environment and traffic. Therefore, each link has a maintenance cost function. Link length, capacity, free-flow speed, and flow determine maintenance cost to a large extent. The amount of money required to expand an existing link can be calculated with a link expansion cost function. A previous empirical estimation of link expansion costs using network data in the Twin Cities metro area during the recent twenty years reveals that link expansion cost is positively correlated to lane-miles of expansion and road hierarchy (interstate, state highway, county highway, etc.), while negatively related to the distance from the nearest downtown (Karamalaputi and Levinson 2003). Those results suggest that link length and capacity should be included in the link expansion cost function, and such function is also subject to local adjustments.

Specific revenue and cost structures in a transportation network provide inputs for investment decisions. Real-world observation suggests the hypothesis that decisions to expand transportation networks are largely myopic in both time and space, usually ignoring non-immediate and non-local effects. This myopic decision process, when applied sequentially, tends to improve the relative speeds and capacity of links that are already the most widely used, and thereby expand their use. The rate and extent of this process is constrained by the cost of those improvements and limited budgets (revenue). From a market economy point of view, transportation investment decisions induce supply (capacity) increases - as population grows and preferences shift, leading to higher demand, suppliers produce more of a good. While surface transportation decisions are often made in the political arena rather than the market, politicians and officials also respond to their customers – the voter and taxpayer. Although over the short-run transportation supply is relatively inelastic; in the long-run it varies. However, it is not known to what extent changes in travel demand, population, income, and demography drive these long-run changes in supply. Answering this induced supply question in transportation is a critical step in understanding the long-term evolution of transportation networks. The output of the investment process would be an updated network where some links are expanded and some degenerated.

If a link is expanded, travel increases on that link both due to re-routing and re-scheduling and due to what is often called induced or latent demand, a finding confirmed at both the macroscopic level (states and counties) (Noland 1998, Strathman et al. 2000, Fulton et al. 2000) and at the microscopic level (individual links) (Parthasarathi et al.

2002). As travel costs for commuters are lowered, the number of trips and their lengths increase. The expanded link with increased travel demand can generate even more revenue which may later result in further expansion on that link. Yet this loop, while positive, should have limits. The diminishing returns in the revenue structure and exponential increases of expansion costs will eventually stop this feedback loop. The opposite is true for degenerated links. All these suggest that reinforcement exists and transportation networks may self-organize into hierarchies. This hypothesis is subject to simulation tests in the following section.

Improving one link will also cause complementary (upstream and downstream) links to have greater demand, and competitors (parallel links) to have lesser demand (and be less likely to be improved). These network effects take time to propagate within transportation networks. They may get reinforced in complex transportation networks, create problems, leave little clue to planners as to the root of the problem, force planners to adopt myopic solutions which may crate even more problems. Such a condition has not been confirmed empirically but it is possible. This again highlights the importance of considering the full ramification of network expansion on future infrastructure decisions. Network effects both complicate the problem and suggest the analysis has to be iterative. Previous changes of the network, economy, demography, and even travel behavior cause a new travel demand pattern and hence new link costs and revenues. Accordingly, a new set of supply decisions will be made, generating new network changes. This loop is repeated until an equilibrium is achieved. When the constant exogenous changes in economy, technology, and population are considered, a transportation network may never reach equilibrium. The evolutionary microscopic network growth process should produce rich dynamics important to anyone who is interested in shaping the future transportation network in a better way.

## 4. A NETWORK DYNAMICS MODEL

In this research, a network dynamics model is developed that brings together all the relevant agents and their interactions to simulate link expansion and contraction. Compared to the earlier network dynamics model due to Yerra and Levinson (2002), this improved model relaxes the assumption of unlimited link capacity, a necessary step that has to be taken to make the model be of any practical importance. The foundation for the model development is the microscopic network growth dynamics described in the previous section. The simulation model can be used to evaluate whether or not important system properties such as hierarchy, self-organization, and growth, actually emerge from decentralized processes. This purpose makes the principles of and modeling techniques for complex systems applicable. There is no universally accepted definition of a complex system. However, it is generally agreed that it consist of "a large number of components or 'agents', interacting in some way such that their collective behavior is not simple combination of their individual behavior" (Newman 2001), which is the case in transportation networks. Examples of complex systems include the economy – agents are competing firms; cities – places are agents; traffic – vehicles are agent; ecology – species are agents. In transportation networks, we model nodes, links, travelers and land use cells as agents. Cellular Automata (CA) and agent-based modeling techniques are commonly employed tools for modeling complex systems (von Neumann 1966; Schelling 1969; Wolfram 1994, 2002) that has been applied to model traffic (Schadschneider and Schreckenberg 1993; Nagel and Schreckenberg 1992). An agent-based structure is pursued wherever possible in the proposed network dynamics model.

An overview of model components and their interconnectivity is shown in Figure 1. A travel demand model predicts link-level flows based on the network, socio-economical and demographical information. Based on the demand forecasting results, links calculate revenues and costs. An investment module then operates and causes annual supply changes, producing an updated network. The modeling process does not have to iterate annually. Other updating intervals can also be used. But yearly supply changes correspond to budgets which are typically decided once every fiscal year. The transportation network is represented as a directed graph that connects nodes with directional arcs (links). The standard notation convention for directed graphs is adopted for the following presentation on the details of mathematical formulations of those sub-models. The directed graph is defined as: $G = \{N, K\}$ where $N$ is a set of sequentially numbered nodes and $K$ is a set of sequentially numbered directed arcs.

### 4.1 Travel demand

Ideally, an agent-based travel demand model in which node, link, and travelers are modeled as interactive agents should be applied to estimate travel demand at the level of links, so as to keep the disaggregate model structure consistent. A previous study (Zhang and Levinson 2003) has proposed such a model with successful application to the Chicago sketch network. However, for two reasons it is not adopted here. First, in its current form, the agent-based travel demand model is not capable of incorporating congestion effects. The second and probably more important reason is that most urban planners currently do not use disaggregate approaches to predict future travel demand in their daily practices. Therefore, a traditional four-step forecasting model is used to predict travel demand at the link level, taking exogenous land use, social-economical variables, and the existing network as inputs. A zone-based regression structure is used for trip generation. The origin-destination (OD) cost table obtained from the previous year traffic assignment is used for trip distribution in the current year based on a doubly constrained gravity model (Haynes and Fotheringham 1984, Hutchinson 1974). The computation of the new OD demand table takes into account the historical impacts of past travel behavior. Travel demand in a given year depends on the demand in the previous year. Levinson and Kumar (1996) elaborate the idea of such a hybrid evolutionary model. In contrast to a traditional equilibrium model, the evolutionary demand updating procedure does not require supply and demand to be solved simultaneously. In this study, the new OD demand is updated by a process similar to the method of successive averages (MSA) (Sheffi 1985, Smock 1962) in traditional traffic assignment procedures. The weights in equation (1) are specified in such a way that OD demand tables in all preceding years are weighted equally toward the current year ($t$) OD demand.

$$d_{ij}^{t} = \left(1 - \frac{1}{t}\right) d_{ij}^{t-1} + \left(\frac{1}{t}\right) a_i O_i b_j D_j f(c_{ij}^{t}) \qquad (1)$$

where:

| | |
|---|---|
| $d_{ij}^{t}$ | demand from origin zone $i$ to destination zone $j$ in year $t$ |
| $O_i$ | number of trips produced from zone $i$ |
| $D_j$ | number of trips destined for zone $j$ |
| $a_i$ , $b_j$ | coefficients in the gravity model |

$c_{ij}^t$ generalized travel cost of traveling from zone *i* to *j*

*f(.)* travel cost impedance function in the gravity model; $f(c_{ij}^t) = e^{-\beta \cdot c_{ij}^t}$

The resulting OD table is loaded onto the current year transportation network through the origin-based user equilibrium traffic assignment algorithm (OBA) developed by Bar-Gera and Boyce (2002). The generalized link cost function comprises two parts, a BPR travel time component and a vehicle toll.

$$c_k^t = \gamma \frac{l_k}{v_k^t}\left[1 + \alpha_1 \left(q_k^t / C_k^t\right)^{\alpha_2}\right] + \tau_k^t \tag{2}$$

where:

$c_k^t$ generalized travel cost on link *k* in year *t*

$\gamma$ value of travel time constant (dollar/hr)

$v_k^t$ free-flow speed of link *k* (km/hr) in year *t*

$C_k^t$ capacity of link *k* in year *t* (veh/hr)

$l_k$ the length of link *k* (constant) (km)

$q_k^t$ average hourly flow on link *k* in year *t* (veh/hr)

$\alpha_1$ , $\alpha_2$ coefficients of the BPR travel time function

$\tau_k^t$ link toll per vehicle (dollar, see equation 4 for details)

The OBA algorithm derives link flows at user equilibrium and generates a new OD cost table which will be used for trip distribution in the next year. In the traffic assignment step, if the relative excess travel cost is less than 0.001, the Wardrop user equilibrium (Wardrop 1952) is considered to be satisfied.

### 4.2 Revenue and cost

Revenue is collected at the link level by vehicle toll. The annual revenue is simply the product of the toll and annual flow. The amount of the toll should be dependent on the length of the link and the level of service. Therefore, the following revenue equation is proposed:

$$\pi_k^t = \tau_k^t \cdot (\omega \cdot q_k^t) \tag{3}$$

$$\tau_k^t = \rho_1 \cdot (l_k^t)^{\rho_2} \cdot (v_k^t)^{\rho_3} \tag{4}$$

where:

$\pi_k^t$ revenue of link $k$ in year $t$ (dollar)

$\omega$ coefficient to scale average hourly flow to annual flow

$\rho_1$ scale coefficient related to the toll level (dollar·hr$^{\rho 3}$/km$^{\rho 2+\rho 3}$)

$\rho_2$, $\rho_3$ coefficients indicating economies or diseconomies of scale

As the free-flow speed of a link increases, travelers are able to save travel time and hence willing to pay a higher toll. However, speed improvements have decreasing returns. For instance, if speed triples from 8 to 24 km/hr, time spent traveling 1 km drops 5 minutes from 7.5 min to 2.5 min. If speed increases 16 km/hr from 88 km/hr to 104 km/hr, the time drops from 41 seconds to 35 seconds – merely 6 seconds – which hardly seems worth considering. Therefore, coefficient $\rho_3$ should be between 0 and 1. Note that with appropriate values for those coefficients, the toll-based link-level revenue structure can also reasonably model centralized revenue collection mechanisms, such as fuel taxes ($\rho_2$ = 1 and $\rho_3$ = 0).

The link maintenance cost function has only two determining factors: link length and capacity:

$$\psi_k^t = \theta_1 \cdot (l_k^t)^{\theta_2} (C_k^t)^{\theta_3} \tag{5}$$

where

$\psi_k^t$ cost of maintaining link $k$ at its present condition in year $t$ (dollar)

$\theta_1$ scale parameter (dollar·hr$^{\theta 3}$/km$^{\theta 2}$)

$\theta_2$, $\theta_3$ coefficients indicating economies or diseconomies of scale

It is also assumed that all links have the same link maintenance cost function. This assumption is obviously not realistic and should be relaxed when local link-specific data are available.

Link expansion cost function is not explicitly specified. If a link is autonomous and its annual revenue is higher than maintenance cost, the link will be expanded in the next year, assuming revenue is not spent elsewhere. If revenue falls below maintenance cost, the link shrinks in terms of capacity reduction and free-flow speed drop. As we will see later in the investment model, those ideas are actually incorporated into a link expansion/contraction function.

### 4.3 Investment rules

The sub-model of network investment decisions can have two aims, describe reality or identify optimal policies. The emphasis in this paper is the prior one, which is in contrast to the long line of research on the Network Design Problem. The network dynamics model must be able to replicate what has happened in reality before it is applied for potential planning purposes. A prototype investment rule (link expansion and contraction function) is examined in which links manage themselves and do not share revenues.

$$C_k^{k+1} = C_k^t \left( \pi_k^t \big/ \psi_k^t \right)^{\lambda} \tag{6}$$

where

$\lambda$ capacity change coefficient

Note that investment decisions in equation (6) are very myopic ones in that links only care about themselves, ignore network effects and spend all revenues immediately. The value of λ actually represents some properties of the link expansion process. If λ is less than 1, it implies that there are diseconomies of scale in link expansion because doubled investment (π) would only produce less than doubled capacity. If λ is larger than 1, economies of scale exists. Capacity changes of a link are usually associated with changes in free-flow speed. Vehicles are able to travel at faster speed on a wider road with less impedance. Free-flow speed and capacity data used by the Twin Cities Metropolitan Council in their regional transportation planning model on more than ten thousand roadway sections were used to study the co-evolution of speed and capacity. A regression model with a logarithm function is adopted (see Figure 2). $R^2$ of the model is 0.7 and both coefficients are statistically significant at level 0.01.

$$v_k^{t+1} = \mu_1 + \mu_2 \cdot \ln(C_k^{t+1}) \tag{7}$$

The predicted free-flow speeds are plotted against data in Figure 2. Keeping component functions such as this one continuous and differentiable in the network dynamics model can save a lot of work for the calibration stage. This is also the reason why an explicit link expansion cost function is not specified and why it is assumed that links invest any extra revenue immediately. However, if these simple continuous functions can not adequately replicate reality, more sophisticated modeling tools should be considered. For instance, link expansion and contraction are in fact discrete events for which a choice model or catastrophe theory may be applied. With updated link capacity and free-flow speed, some factors influencing travel behavior such as link travel time and link toll change. Theses supply shifts, combined with preference, economical growth and demographical changes, give rise to the emergence of a new demand pattern.

So far, a complete cycle of the network evolution process has been modeled. This cycle repeats itself year after year. Simulation of these cycles can reveal various emergent properties of transportation network growth. The proposed network dynamics model can and should be calibrated and validated against observed time-series network and land use data. The calibration procedure may consist of two stages. The parameters in the sub-models (demand, revenue, cost, and investment) are estimated from empirical network data. These estimates then form a starting solution for an iterative optimization routine with an improving search algorithm. Finer adjustments to the model system and parameters should be undertaken based on an objective function, which can minimize the difference between the observed data and the model ability to predict which links were improved and by how much. In brief, the model parameters form a space which can be searched systematically to find a best fit between actual and predicted link expansions and contractions. The transportation network data in the Twin Cities metro area have been collected between 1978 and the present in digital format, while data collection work on corresponding land use and economical information is ongoing. In the most recent (2000) Twin Cities transportation network, there are 7976 nodes and 20914 links. A bit more than 600 link expansions have taken place since 1978, which implies the Twin Cites transportation network is mature.

Though a rigorous calibration work can not proceed unless all required data are collected, simulating the model with the available Twin Cities network data can still provide valuable information regarding the modeling concept, structure and feasibility on a large-scale realistic network. The values of model parameters in these preliminary runs are based on either empirical estimation or our best understanding of the economies and diseconomies of scale in the network growth process, which are summarized in Table 1. The simulation experiments also provide opportunities to examine some qualitative properties of network dynamics.

## 5. SIMULATION EXPERIMENTS AND RESULTS

Four experiments are set up with different initial conditions and restrictions on link contraction. It is assumed in all experiments that there are no exogenous changes in land use, economy and population. The fixed land use, economy and population in the model are based on 1998 Twin Cities Metropolitan Council data. Let us imagine we were planners in 1978 who are interested in network growth twenty years from "now" (year 1998). The 1978 network thus becomes the "existing" network. So, in essence, these four experiments set up scenarios in which "estimated" land use twenty years from "now" is applied to the "existing" network. Using the real 1978 network as the initial condition for the simulation model (Experiments 1 and 2) allows us to observe whether and how this real-world network achieves equilibrium. The real 1978 network already exhibits hierarchies in that a few important roads carry the bulk of traffic while most roads have relatively low speed and volume. In order to see how network hierarchies emerge in the growth path, the other initial condition is the 1978 network with a uniform capacity of 400 vehicle/hour, which is the capacity of the narrowest link in the 1978 network. The adoption of two initial scenarios can also reveal if starting conditions significantly affect the future growth of a transportation network. In the investment model, link contraction occurs as long as the collected revenue is insufficient to maintain a link at its present condition. However, in reality links usually do not shrink – once you build it you can not easily abandon it. The presence of this practical constraint is considered and applied to two of the four experiments (Experiments 2 and 4). Comparison of simulation results with and without the link contraction restriction shed some light on future refinement of the investment rules. In the simulation, if the network does not change in two consecutive years, the simulated network evolution process stops and an equilibrium is achieved. It is also possible that the network does not converge and changes constantly among two or more distinct states.

The four simulation experiments are carried out on a personal computer with a Pentium 4 processor at 1.7 GHz, slower than standard personal computers currently sold in market. On average, it takes about twenty minutes for each simulation iteration. The traffic assignment algorithm consumes a major portion of the running time. There are a lot of link expansion and contraction activities at the beginning of the evolution process. As we can see in Figure 3, thousands of links are expanded and contracted in the first several years following 1978. However, the network settles itself very quickly, and after about 25 years fewer than a hundred links still experience (relatively small) changes in capacity and free-flow speed. In order to achieve the strict equilibrium defined as a network with no more capacity changes, it is necessary to continue the iterations for many more years at any network as large as the one in the Twin Cities metropolitan area. But all significant changes occur during the first 20 years. It is clear the network dynamics model is approaching an equilibrium smoothly. It is probably not practical (with this level of computer reality) to execute the model until a strict equilibrium is achieved. A goal function can be set up to determine the stopping point of the simulation. For instance, further iterations are not considered if the average percentage change of link capacity becomes less than 0.001. The remainder presentation of the simulation results only focus on the network dynamics between 1978 and 1998 since most important changes take place during this period.

Road hierarchies clearly emerge in all four experiments (see Figure 4). In the predicted 1998 networks, most roads have low capacity and carry low flows, while only a few roads are expanded to very high capacities and carry the bulk of traffic. Experiment 1 and 2 start from the 1978 network with real capacity and hence the hierarchical structure is already present at the initial condition because the construction work of most freeways in the Twin Cites had been completed by 1978. It is, therefore, not very surprising to see the predicted 1998 network hierarchies conform very well with the observed 1998 data. With accurate network data in the starting year (1978) and good exogenous forecasts of land use and economic growth in a future year (we actually observed the 1998 land use), the proposed network dynamics model with very simple decentralized cost, revenue and invest functions provides satisfactory forecasts of link hierarchies in the future year. It is interesting to see that hierarchies also emerge in Experiments 3 and 4 where the starting condition is a uniform capacity network. The predicted hierarchies in these two scenarios are actually very close to the observed ones for lower-level roads. The results from Experiments 3 and 4 also suggest that if planners in the Twin Cities could design a brand-new network to serve the existing travel demand and replace the existing network, they would build many fewer roads with very high capacities, as seen on the right side of the two graphs. This finding may be somehow not very meaningful due to the big "if". How the network arranges itself in a hierarchical pattern from a uniform status is a really interesting question. To answer that question, the growth path of the Twin Cities network in Experiment 4 is presented in consecutive maps where changes in road capacity are shown with lines with different weights (Experiment 3 gives almost the same results and is therefore not shown).

For those who are not familiar with the Twin Cities metropolitan area, a brief description of the features of the region may be helpful before the maps in Figure 5 are examined. Two traditional central business districts, downtown Minneapolis and downtown Saint Paul, are approximately ten kilometers from each other. The Minnesota River meets The Mississippi River right in the city. At the confluence point of the two rivers is the region's international airport. A new suburban business area, downtown Bloomington, also emerges near the airport. The three downtowns, as well as the rivers are shown in the base year network, the first map in Figure 5. After four years, the model predicts that some roads are expanded. The location of these expansions tells us much about how road hierarchies emerge even from a uniform network. Natural barriers, such as rivers in this case, are sources of unbalanced road construction. It is clear that bridges are able to attract more flow than other roads in the network and hence get expanded first. Network effects then drive more flow to the roads emanating from bridges, for instance the roads along riverbanks. If one carefully examines the roads surrounding the airport, the circle just west of the river conflux, it is evident these roads are also able to generate more revenues than an average road and are expanded early in the evolution process. The rule of the airport here is much like some natural barriers such as mountains, because they all direct more flow to bypasses. The second source of hierarchy comes from activity centers. The three downtowns with high density of jobs and other activities are the areas with intense road expansions in the years following 1978. Finally, the fact that all major road expansions between 1978 and 1982 take place in the central area of the region suggest that boundary effects also contribute to the formation of road hierarchies. Though we live on a round globe, even the largest metropolitan area today is still better modeled as a planar surface. Travel demand on a limited plane is not uniform. Most trips originating from the edges of the city are inward trips and destined for activity centers located relatively closer to the geographical center of the region, while trips emanating from areas in the middle of the city are distributed along all possible directions. The asymmetry in demand patterns is the third source of road hierarchies identifiable from the second map. Again, network effects will help propagate the hierarchies created by those three sources throughout the whole network over the years. Twenty years later, road hierarchies can be found virtually everywhere in the network (see the third map).

Congestion is undesirable in a network and attracts a lot of attention in network analysis. In Figure 6, volume capacity ratios (VC ratios) of all roads in the network after twenty years of evolution are plotted in a histogram. The observed 1998 data suggest that most roads carry flows well below their capacity and a few roads operate at VC ratios near or slightly higher than one. Practically, over a long period of time, no road can carry flows more than its capacity. The presence of VC ratios larger than one in the model is the result of inadequate description of road travel delays and scheduling adjustments in the traditional four-step travel forecasting model. Experiments 1 and 3 allow road degeneration, the results from which show a narrow range of VC ratios, suggesting a more uniform distribution of congestion in the network compared to the observed data. Note that the model does not say that at equilibrium a uniform distribution of VC ratios will be achieved. Roads have similar VC ratios in Experiments 1 and 3 but not the same. Experiments 2 and 4, with a constraint on road contraction, obviously predict congestion much better than their counterparts without the constraint. Once a road is expanded but demand later does not justify the capacity after the expansion, the road is still going to be maintained and capacity reduction is less likely to happen. Furthermore, in the real world capacity expansions are discrete (1 lane, 2 lanes), while here they are modeled as continuous. Therefore, a constraint on road degeneration in the model should make it more realistic. The spike near VC ratio of one is still present in Experiments 2 and 4. This is because the same revenue and cost functions are applied to all roads. In reality, it may be more expensive to expand some roads than others and hence different levels of congestion are observed. This suggests that cost and revenue functions in the model should be adjusted according to local conditions.

The need for differentiated cost functions is identified again from the comparison between the predicted road expansions from 1978 to 1998 and the ones that actually happened. In Figure 7, the prediction results from Experiments 1 and 2 are compared to the observed data. Although, the model successfully predicts construction on several freeway segments, it forecasts more expansions on roads already having high capacities (freeways) while fewer expansions on arterials than reality. Either the expansion costs of arterial roads are overestimated or the costs of freeways are underestimated in the model. At this point, we are not arguing that the model predicts what should have been done. It must be able to describe reality first before it can be used as a normative tool.

Finally, the impacts of starting conditions and constraints on the predicted network dynamics are examined in Figure 8. Clearly, they do matter. By comparing the four graphs vertically, i.e. Experiment 1 against 3, and 2 against 4, we find that different initial networks results in quite different networks at equilibrium. A horizontal comparison of the graphs reveals the influence of the presence of the restriction on road degeneration.

## 6. CONCLUSIONS

A transportation network is a very complex system that consists of a full spectrum of various sub-systems, the properties and behaviors of which are already hard to forecast. Efforts put into travel demand forecasting, network design problems, and revenue policies by numerous researchers are evidence of such difficulties. Predicting the growth of transportation networks is difficult because it requires us to consider almost all sub-processes involved in network dynamics. Understanding the true relationships between supply and demand in transportation networks is the crucial task in theoretical developments of network dynamics models. The difficulty also comes from practical issues, such as available data for model calibration and validation. Socio-economical, demographical, land use and transportation network data many years ago in an urban area must be collected and coded consistently over time. Several unresolved issues further complicate the problem and the foremost one – Is network growth simply designed by our planners or it can be indeed explained by underlying natural and market forces? In light of this debate, we would like to view this paper as a proof of concept that some important system properties, such as road hierarchies and self-organization in transportation networks, can be predicted through a microscopic evolutionary process, a demonstration that such a microscopic agent-based model of network dynamics can be feasibly applied to large-scale realistic transportation networks, and an enquiry into how this concept can be realized and produce useful modeling tools for planners. Growth of economy, population, and cities has been intensively studied and knowledge accumulated from such studies has greatly aided planners. Traditionally, transportation networks have been assumed to be static or predetermined in analysis of urban areas. A model of transportation network dynamics can reveal more completely the impacts of today's planning decisions in the future.

The present paper explores only the rise and fall of existing roads (maybe the rise and rise of existing roads given the preliminary simulation results), leaving the questions of how new roads are built and new nodes are created in transportation networks to be answered by future studies. The process of road development and degeneration at the microscopic level is analyzed and an agent-based simulation structure seems to be appropriate for modeling that process. In order to better describe reality, a systematic way to adjust cost and revenue functions based on area-specific factors such as type of roads, land value, and public acceptance should be considered. Calibration of the network dynamics model is still part of an on-going study.

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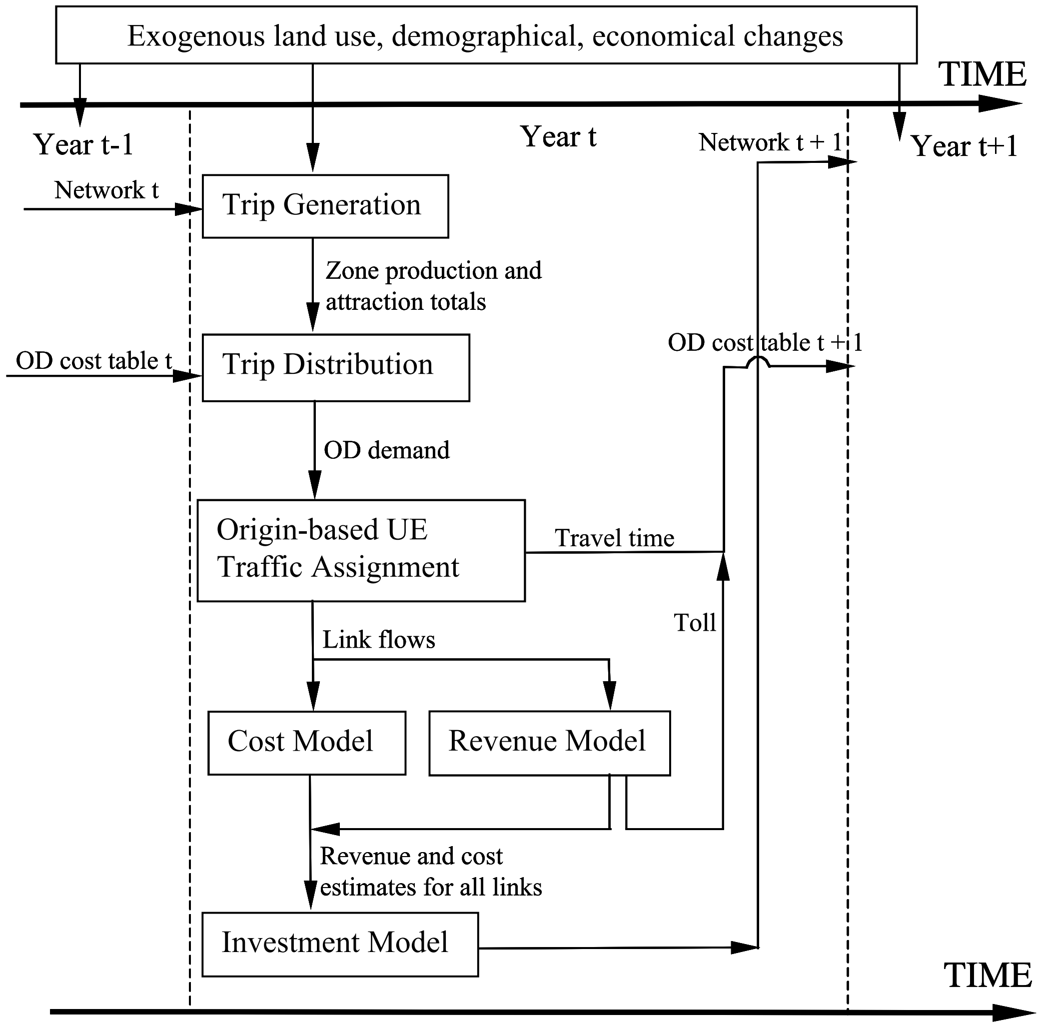



*Figure 1.* Flowchart of the Transportation Network Dynamics Model

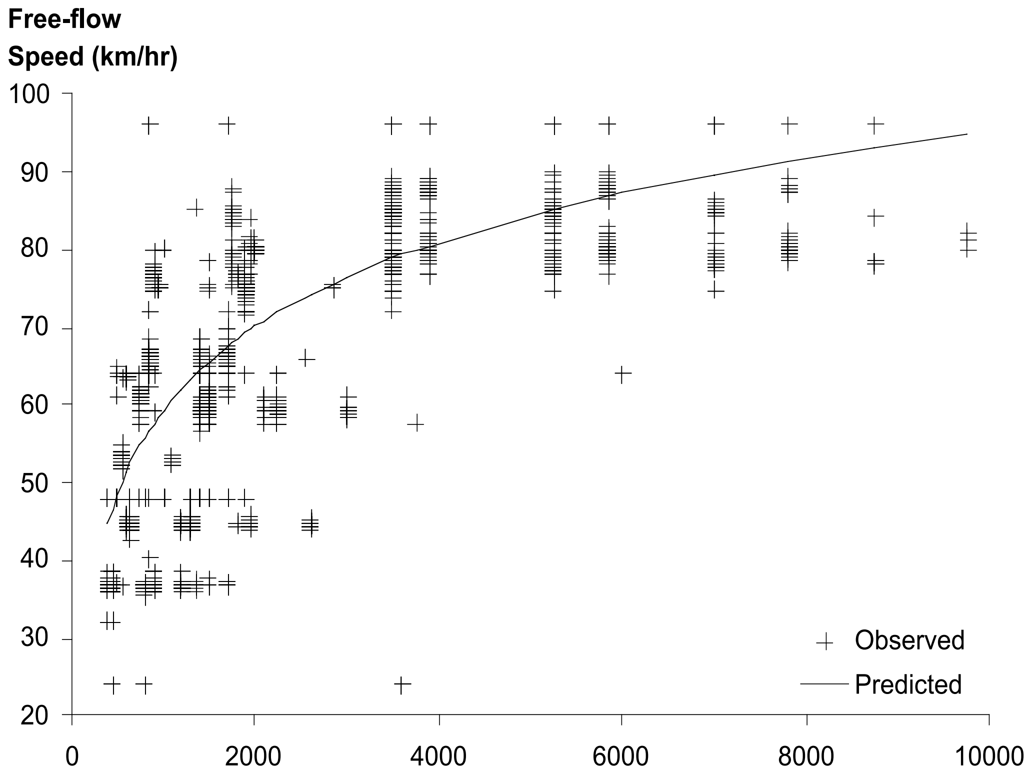



*Figure 2.* Link Capacity and Free-Flow Speed Relationship: Observed vs. Predicted

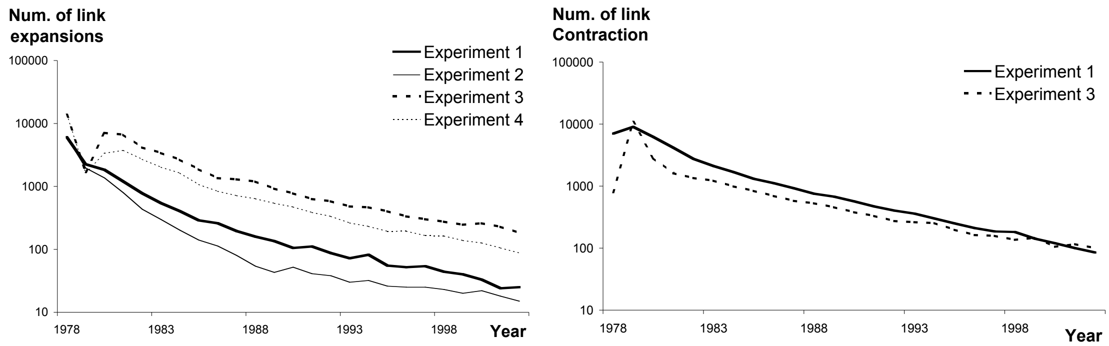



*Figure 3.* Convergence Properties of the Network Dynamics Model

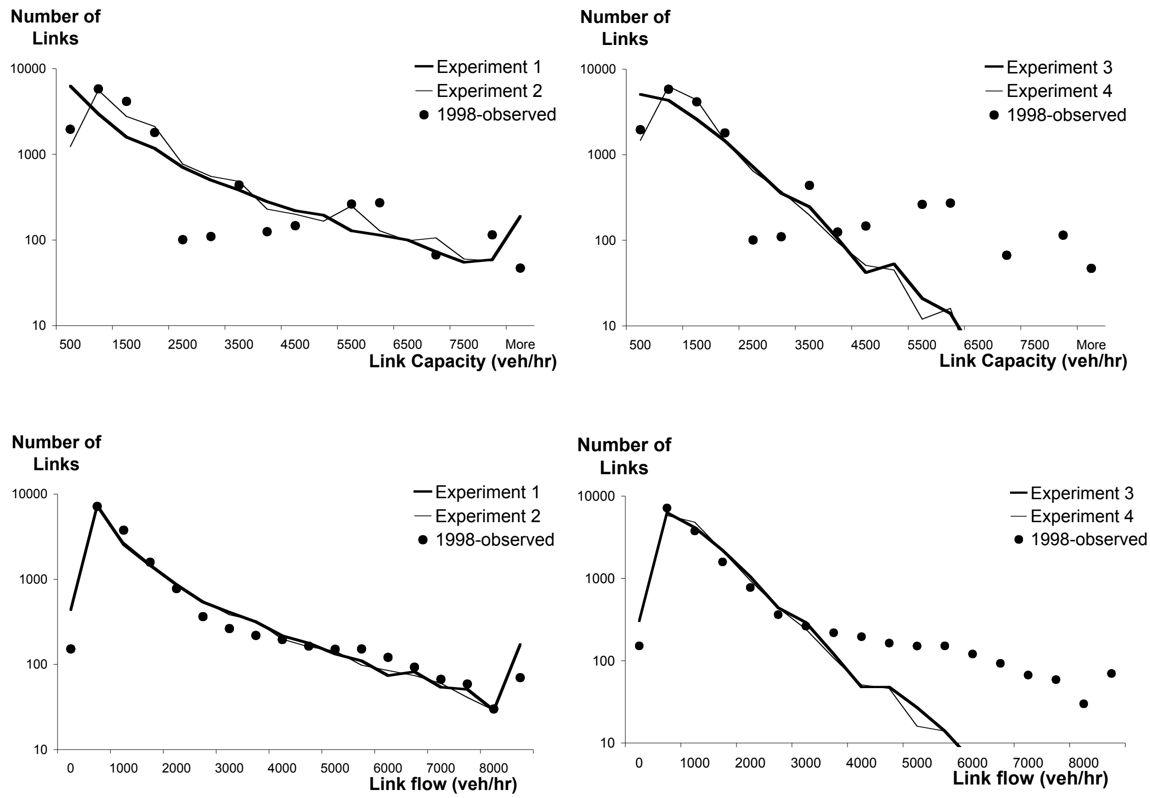
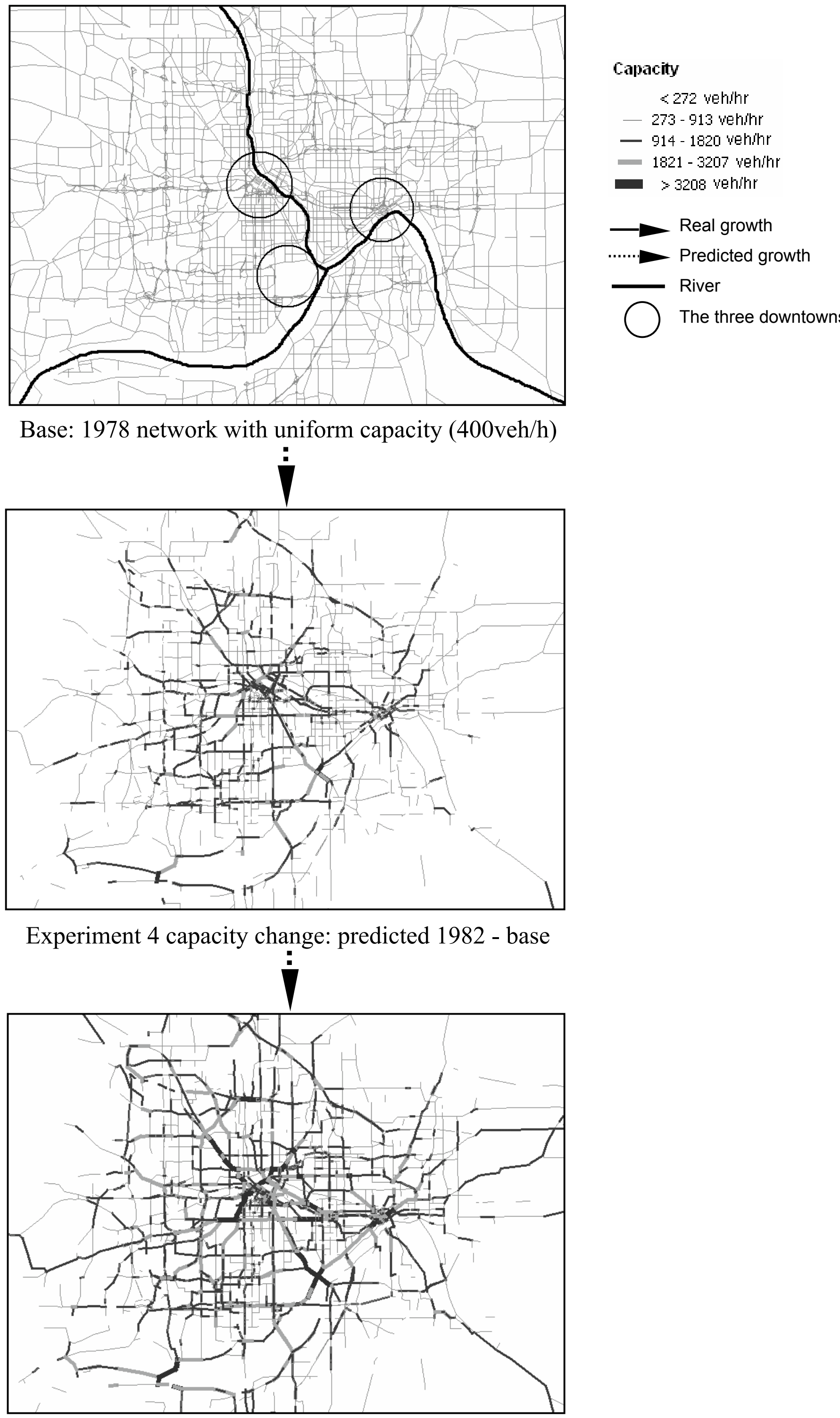



*Figure 4.* Link Hierarchies after 20 Years




Base: 1978 network with uniform capacity (400veh/h)

Experiment 4 capacity change: predicted 1982 - base

Experiment 4 capacity change: predicted 1998 - base

*Figure 5.* Emergence of Hierarchies in Experiment 4

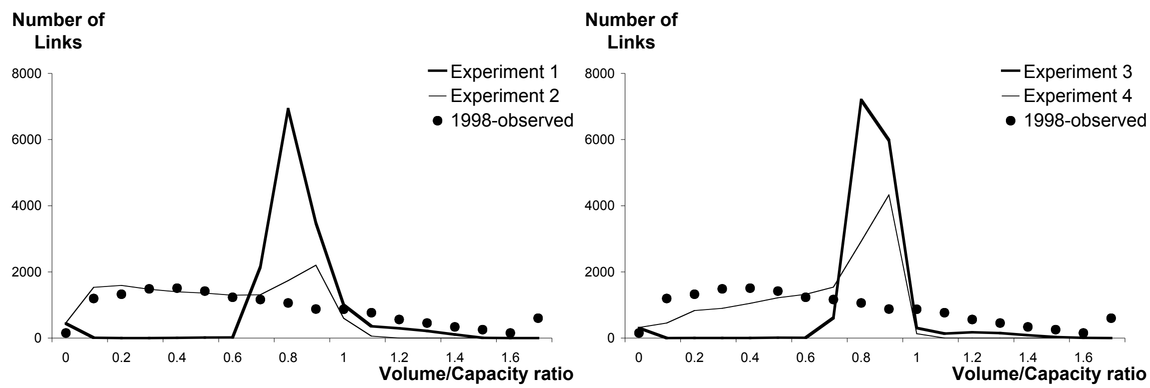



*Figure 6.* Network Congestion after 20 Years

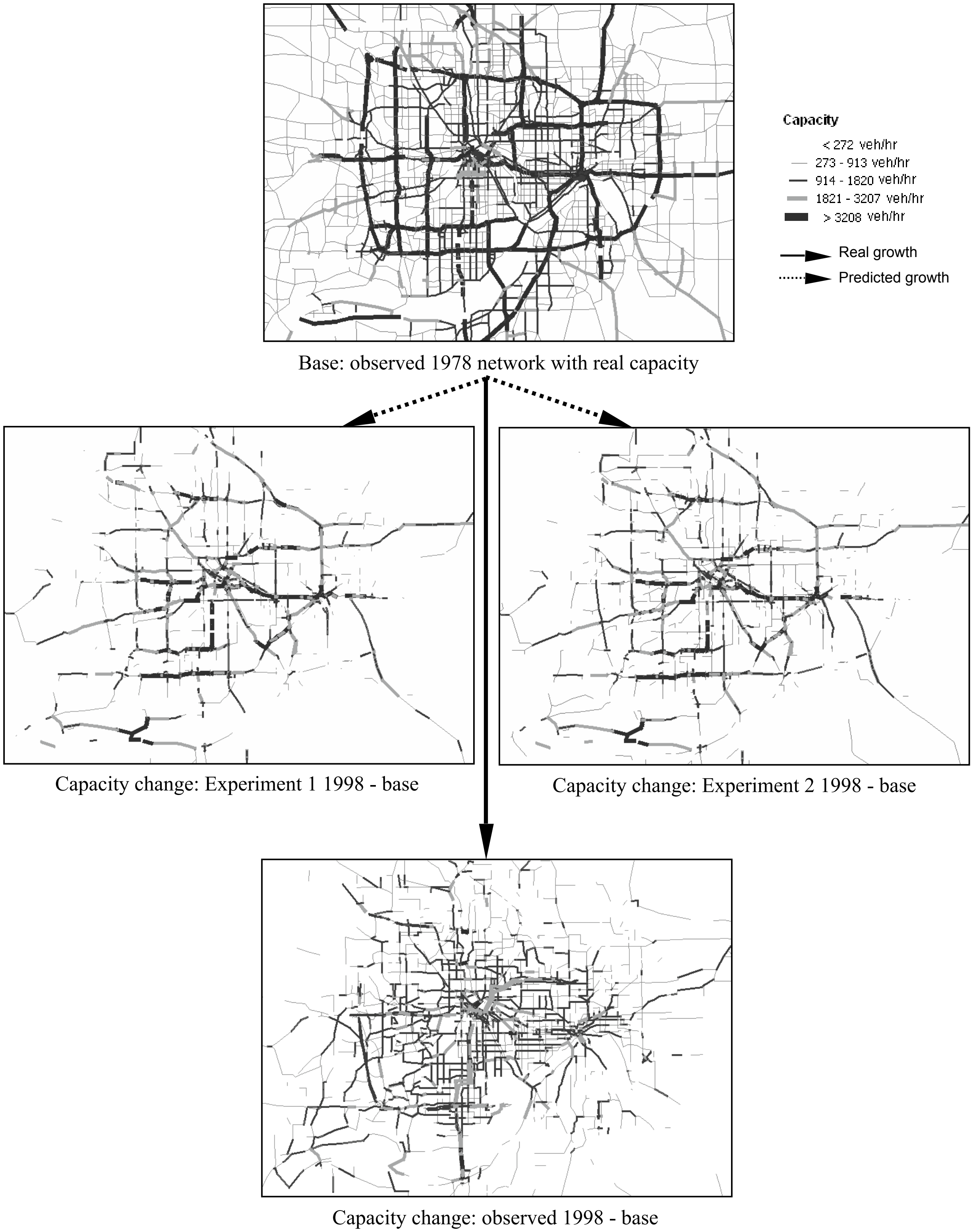
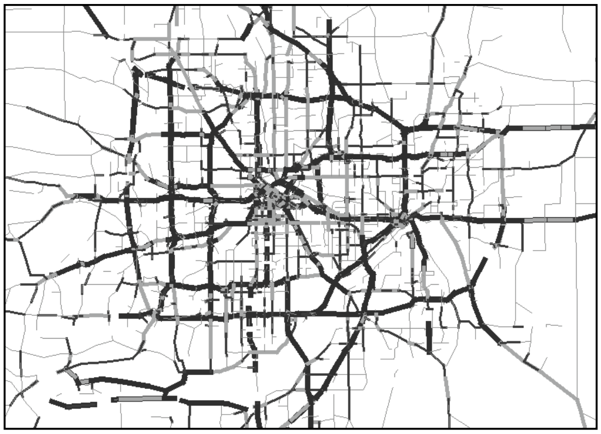
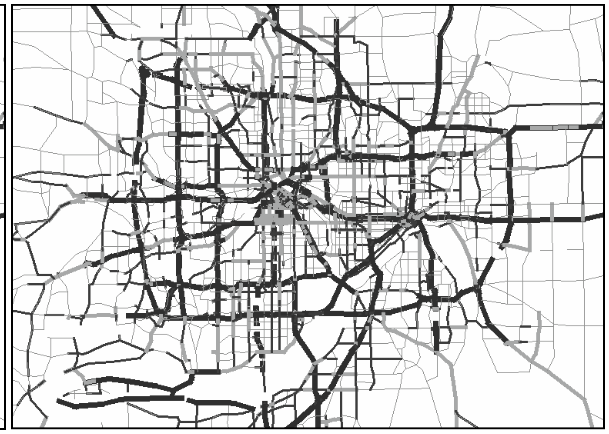


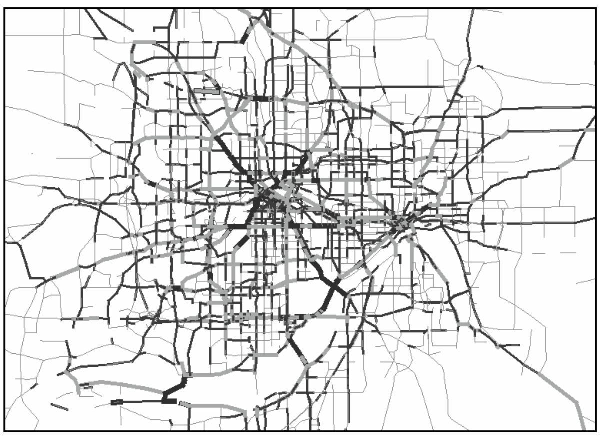

*Figure 7.* Experiment 1 and 2 vs. Observed Network Growth after 20 Years



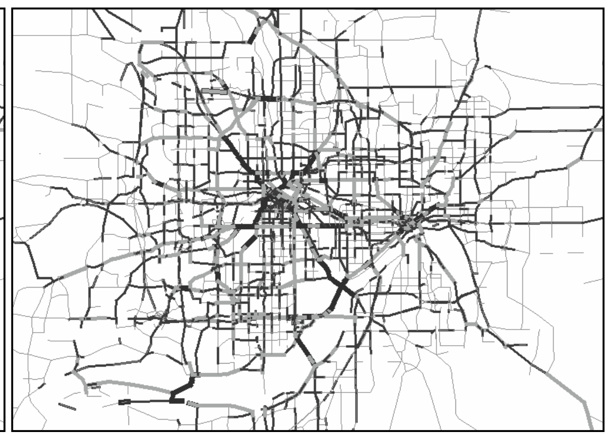
Experiment 1: predicted 1998 network



Experiment 2: predicted 1998 network



Experiment 3: predicted 1998 network



Experiment 4: predicted 1998 network

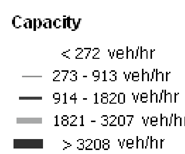



*Figure 8.* The impacts of starting conditions and constraints on network growth

*Table 1.* Coefficients used in the experimental runs of the network dynamics model

| Parameter | Description | Value | Source |
|---|---|---|---|
| $\gamma$ | value of travel time constant ($/hr) | 10 | Empirical findings |
| $\alpha_1$ , $\alpha_2$ | coefficients in the BPR function | 0.15, 4 | BPR |
| $\beta$ | coefficient in the gravity model | 0.1 | Empirical findings |
| $\rho_1 \cdot \omega$ | Combined scale coefficient in revenue model (dollar·hr$^{\rho 3}$/km$^{\rho 2+\rho 3}$) | 1 | Scale parameter |
| $\rho_2$ | Power term of length in revenue model | 1 | CRS of link length |
| $\rho_3$ | Power term of speed in revenue model | 0.75 | DRS of level of service |
| $\theta_1$ | Scale coefficient in cost model (dollar·hr$^{\theta 3}$/km$^{\theta 2}$) | 20 | Scale parameter |
| $\theta_2$ | Power term of length in cost model | 1 | CRS of link length |
| $\theta_3$ | Power term of capacity in cost model | 1.25 | IRS of capacity |
| $\mu_1$ , $\mu_2$ | coefficient in the speed-capacity regression model | -30.6, 9.8 | Empirical estimate based on Twin Cities data |
| $\lambda$ | capacity change coefficient | 0.75 | DRS in link expansion |

*CRS, DRS and IRS: constant, decreasing, and increasing returns to scale*

*Table 2.* Four simulation experiments

| Allow for link contraction? / Initial condition | Yes | No |
|---|---|---|
| 1978 Twin Cities network with real 1978 capacity | Experiment 1 | Experiment 2 |
| 1978 network with uniform capacity (400veh/h) | Experiment 3 | Experiment 4 |