Traffic Flow Landscapes

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Abstract

Major metropolitan areas and constituent independent jurisdictions face the problem of providing efficient transportation for their residents and in-and-out commuters. A typical trip taker spends considerable time on the road to reach the workplace and other destinations. Though it may seem counter-intuitive, adding more links to existing road networks and/or increasing traffic capacity by adding lanes does not necessarily decrease travel times (eg. Braess’ paradox). But it is certain that a dense redundant network of roads would provide a trip taker with alternate routes when traffic incidents occur. These types of questions raise the question of, how to evaluate the flow characteristics of the entire road network of a jurisdiction and its larger region in keeping the traffic moving? Further, how may the impact of adding more links/lanes or the blocking of existing links/lanes be best measured?

To answer these and related questions, we propose a methodology to evaluate a fitness criteria for road networks based on Kauffman’s biological NK model (1993). We specify a transportation road traffic flow landscape analogous to the fitness landscape of the NK model. Using the transportation road traffic flow landscape we derive a road fitness index that can be used to evaluate either the entire road network’s traffic flows or subparts of such network’s traffic flows. We explore the possibility of investigating traffic flow landscapes to search for optimal routes to clear traffic. Finally we describe an approach for applying the theoretical framework developed in the paper to the traffic conditions on the road network of the city of Fairfax, Virginia.

Key Words: Fitness Landscapes, NK Model, Genotype, Gene, Self-Organization, ITS Technology

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INTRODUCTION

Urban road networks are characterized by traffic congestion, incidents and accidents (Lave, 1985), resulting in travel delays for commuters and other trip takers on urban road networks (Downs, 1992). The interaction costs of such congestion in a regional economy is enormous and factoring in work time lost to business and commuters makes the sums astronomical (Arnott, Small, 1994). Increasing capacity of existing freeways by adding more lanes is not always possible or environmentally desirable and does not always ease the delays. The much studied Braess's paradox tells us that congestion may increase as capacity is increased instead of reducing it (Murchland, 1970). However the costs of incidents and accidents could be reduced if the trip taker is provided with timely warnings of such events. ITS traveler management systems hold the promise to provide information on traffic conditions. However, providing the data on traffic conditions alone may be of little help if there is no underlying processing framework to evaluate and disseminate the processed information. The literature on what is referred to as dynamic network flows modeling is increasing rapidly. There have been many attempts to model both the dynamics as well as the equilibrium/disequilibrium network flow conditions that exist on urban road networks. Both analytical and simulation/experimental studies have been carried out (Friesz, Bernstein and Stough, 1996; Friesz, Bernstein, Smith, Tobin and Wie, 1993; Friesz, Bernstein, Mehta, Tobin and Ganjalizadeh, 1994; Mahmassani, 1995; Mahmassani, 1990; Mahmassani, Hu and Jayakrishnan, 1992; Mahmassani and Peeta, 1992; Koutsopoulos, 1995.)

Historically dynamical behavior of traffic flows and its theoretical framework was developed by Herman, Montroll, Potts and Rothery (1955), Newell (1955), and Lighthill and Whitman (1955). Herman and Prigogine (1971, 1979) also developed a kinetic theory of traffic and road networks using statistical mechanics as an underlying analytical framework. Herman and Lam (1971) proposed an analytical framework of traffic flow based on the Boltzmann theory from physical sciences. The development of various theories of human and machine interactions on the roads have been investigated (Herman, 1966) and a vast body of work related to computer simulation as well as experimental and
field test/verification has been conducted (Herman, 1991; Mahmassani and Herman, 1990; Mahmassani, Jayakrishnan and Herman, 1990; Mahmassani, Williams, Herman, 1987).

In the early 1980s, Herman proposed the idea of looking at road traffic as a self organizing phenomenon (Herman, 1982). Workday traffic flows on roads show the morning and evening rush hour peaks with the intervening troughs for the rest of the day. Thus at the macroscopic level most metropolitan traffic flow patterns seem to show similar profiles. However, it is quite unlikely that the traffic patterns on a given day match exactly those of the previous or following workdays. Indeed the stochasticity of traffic patterns arises mainly as a consequence of "noncollaborative" trips taken by commuters. The word "noncollaborative" is used here in the following way. Typically, the total number of trips on any given workday run into several hundreds of thousands. Commuters are "aware" of other commuters' plans to travel only to the extent that they are going to share the limited resources of time and road space with other unknown commuters. The commuters do not inform each other of their intended trips and schedules and plan accordingly for their journeys. Most of the time, commuters follow a loose schedule that they create out of their day to day experiences of trips on the roads. Thus, traffic is an aggregate of the multitudes of decisions executed by commuters in a noncollaborative manner; there is no master plan that exists or can be created to regulate traffic on the roads. "How does one develop a traffic flow model that takes into account the stochasticity of the trips?"

One of the possible approaches would be to reduce the randomness of trips by actually simulating each and every commuter's trips - the so called microsimulations approach (for pioneering work refer Chang, Mahmassani, Herman, 1985; Mahmassani, Chang, 1987) and the TRANSIMS model under development by the transportation group at Los Alamos National Laboratory (Berkbigler, Loose, Davis, Williams, 1995; Smith, Beckman, Anson, Nagel, Williams, 1995.) The TRANSIMS model is a hierarchical microsimulation model that has incorporated the so called real time trips attributed to users of the road network. It is a very ambitious project with great potential, but depends on a vast amount of computing power.
It is worth noting that there is a parallel and growing trend in many other fields towards developing new types of analysis/models rooted primarily in complexity theory: evolutionary or self organizing systems (Holland, 1995; Kauffman and Macready 1995; Krugman, 1994, 1995; Arthur, 1989; Langton, Minar, Burkhart, 1995; Rasmussen, Barrett, 1995); including fractals (Mandelbrot, 1982; Batty, Longley, 1986); cellular automata (Das, Mitchell, Crutchfield, 1994; Mitchell, Crutchfield, Hrabar, 1994); neural networks (Hopfield, 1982; Dougherty, 1995), genetic algorithms, emerging/evolutionary biological and computational models (Macready, Siapas, Kauffman, 1996, Macready, 1995; Crutchfield, Mitchell, 1994; Jones, 1995) and spin glasses (Edwards, Anderson, 1975; Sherrington 1971; Mattis 1976; Fisher, 1992; Mydosh, 1993) and their application to the flow theories (Kulkarni, Stough, Haynes, 1996) among many other applications (Bounds, 1991; Wolynes, 1992). There seems to be a push towards analyzing large and complex systems to see if these systems show spontaneous adaptive behavior towards self organization and their sensitivity to maintaining good fit metastable equilibrium states.

In this paper we explore the approach of spontaneous self organization and adaptation as applied to large scale, complex road traffic networks and how the use of ITS related technologies may help in maintaining an overall good fitness of the traffic networks for the benefit of both the users and the traffic managers. The traffic flow landscape model described in this paper is based on the NK fitness landscapes of Kauffman (1993). It uses the randomness of traffic as one of the endogenous inputs. Second, just as biological processes do not operate on the assumptions of precise inputs and outputs while adapting to the changing environments, the traffic fitness landscape model proposed in this paper has capacity to adapt to the changing traffic conditions and provide primitive outputs that help with traffic management of the road network. The traffic changes may be either due to planned activities (eg. blocking of lanes for repairs), unplanned activities (eg. accidents) or other unforeseen events and the model provides useful answers that are independent of network size. One of the measures we propose is to create a traffic flow index that could serve as a barometer of the traffic conditions on road networks at any instant. The traffic flow index could be used across a network or
within networks to compare the adaptability of traffic systems for ever changing traffic and network conditions.

To improve transportation management, it is proposed to develop an analytical rugged traffic flow landscape model for urban road networks based on the NK model (Kauffman, 1993). Figure 1 shows a schematic of the information flow in the proposed NK model while figure 2 shows the operational elements of a real time metropolitan traffic management center.

Figure 1: Input data on traffic flow on road links

Figure 2: TMC

Figure 1 and 2 illustrate Traffic Management Centers (TMCs) that gather data on traffic flow conditions on road links using various types of sensors. The TMC’s information process handles data similar to that required in the NK model and evaluates/ranks the road links performance and provides advice to the users of the road network.

This data flow system and real time traffic management process enables the development of a traffic flow index $\Gamma$ for a part of or for an entire network of roads. Any flow change in the existing road network (or for specific links) could then be evaluated in terms of changes in this traffic flow index. The index may serve as a decision support tool since one could easily simulate the impact of the selective blocking of the links of the network or the adding of extra links. Further, one may be able to compare the existing road networks across all the jurisdictions in a metropolitan area and rank these on the basis of the traffic flow index. In the case of incident management it could provide a measure of
how long it takes a network to recover from an incident (resiliency). It will make it possible to decide whether there is a global optimal solution for a traffic network, and if not; then how many sub-optimal solutions exist for the network as well as individual links and how the network can be adjusted to achieve near global solutions, and how long it would take to achieve these conditions. With this information on network flows, one could use this as input for such ITS technologies as ATMS and ATIS.

Fitness Landscapes

The word “Landscapes” has topological connotations. Even though, the word evokes a visual that everyone relates to in different ways, there are certain properties that are common to many landscapes, for instance the landscapes have morphology such as multiple peaks (either sharp or gentle) and troughs and connecting ridges. The topology of a region makes it clear that to reach point ‘P’ on one of the peaks from point ‘Q’ on another peak involves finding the best possible route between these two points, avoiding regions of valleys. Alternately, one may want to avoid the peaks and reach a desired valley region. The landscape image suggests that there may be more than one peak that may suffice for a criteria and that not all peaks and valleys are reachable easily. Thus it may appear easy to perceive of assigning a fitness value to a criteria and then create a visual image that has peaks for good fitness values and valleys for bad fitness. “How does one use the idea of fitness to create traffic landscapes?”

In the next section a brief explanation of an NK fitness landscape model is outlined as a basis for developing a traffic fitness landscape model. Next the landscape model is applied to the road network for the city of Fairfax. Conclusions and Future work are discussed in the final section.
THE NK MODEL

The NK model of the evolutionary biologist Kauffman explains how a variety of genotypes is able to adapt to so called rugged fitness landscapes of the environment in which these genotypes evolve. The N stands for number of genes and K stands for number of interactions any single gene has with other genes. Each gene may have L alleles. Alleles are the variations in each gene that give rise to a physical trait such as eye color of blue, brown, black etc. Each gene contributes to the overall fitness of a genotype. At the same time each is influenced by K genes that are either nearest neighbors or are spatially separated from the gene. Thus the result of all the interactions between N genes and K influencing genes is a fitness landscape with multiple peaks and valleys. The peaks are associated with fitness values. Depending on the value of K, the landscape varies from a simple profile (K = 0) to one with a very complex profile (K = N-1). The former (K=0) refers to an environment in which each gene is independent of all its neighbors and the latter refers to a situation when each gene is influenced by all the genes (K=N-1) in a genotype. After defining a few terms used in the context of traffic on road networks in the next section, we develop the traffic flow landscape model.

Definitions

An urban region's road network consists of many types of roads - highways, major and minor roads, arterials and connecting roads. For a traffic fitness landscape we include roads/segments that are referred to as primary and secondary roads/segments as described in the TIGER/Line™ files Census Feature Class Codes (1992). A set of links are segments of these highways, major roads and arterials. The following terms are used interchangeably. The links/segments of roads are analogous to genes. The possible levels of service (Highway Capacity Manual, 1985) are referred to as alleles as in biology. Thus for example, levels of service A through F are the six alleles of a link (gene). According to the Special Report 209 of Highway Capacity Manual, "the concept of levels of service is defined as a qualitative measure describing operational conditions within a traffic stream, and their perception by motorists and/or passengers. A level-of-
service definition generally describes these conditions in terms of such factors as speed and travel time, freedom of maneuver, traffic interruptions, comfort and convenience, and safety.” (1985). To quantify the qualitative concept of levels of service we suggest a very simple method in Appendix A based on fractals. The numerical values of levels of service are used as fitness measures assigned to alleles of links. A set of \( N \) links with \( L \) number of alleles has \( L^N \) possible configurations. (In terms of levels of service A through F, we have \( 6^N \) possible configurations for \( N \) link network.) Each of these configurations is referred to as a genotype. Each genotype is one allele different than its neighboring \( D= N(L-1) \) other genotypes and hence can be said to carry a mutant gene. One may associate with each allele of a gene a fitness value. Thus a genotype's total fitness is expressed as an aggregation of the fitness values of its genes/ alleles depending on the value of \( K \), the interaction parameter.

**TRAFFIC FLOW LANDSCAPE MODEL**

Consider an urban road network of \( N \) links. The links can be either road segments between mile stones or distances between consecutive traffic signals or any other measure that has been defined with consistency across the network. The traffic flow levels, which can be operationalized using the levels of service (Highway Capacity Manual, 1985), are the levels of service \( L \) of each link. Thus each link can have A through F levels of service. For illustration purposes let us restrict the flow conditions to two levels of service. For coding convenience let us identify these conditions in a binary format 1 (full flow) and 0 (zero flow). Then at any instant a set of links with specific flow levels constitutes a configuration of the entire road network among all possible configurations. For example, for \( N \) links with \( L \) flow levels, the number of possible configurations is given by \( L^N \). For two types of flows (identified by 0 or 1) the total number of possible configurations of link flows is given by \( 2^N \). Let \( K \) refer to number of links interacting with each other. Next we explain the road configurations for different values of \( K \).
1. $K=0$ Case

Let us assume that a link with full flow condition (1) contributes +1 to the overall fitness of the network, and a blocked link (0) contributes -1 to the overall fitness of the network. Note that in this case $K$ the number of interactions among the links is assumed to be zero, i.e., each link contributes to the overall fitness independent of all other links. The entire network configuration may be represented as a combination of 1 and -1s. The total number of possible states is given by $2^N$. Thus, there are two trivial states that one can find for the $N$ link network. One of these states has all the links blocked thus the network links can be represented by the following vector:

$$\left( -1, -\frac{1}{2}, -\frac{1}{3}, \ldots, -\frac{1}{N} \right),$$

and the total fitness $M_G$ is given by the following:

$$M_G = \sum_{i=1}^{N} -1_i = -N.$$  \hspace{1cm} (2)

The other state has all the links in the free flow condition and may be represented as the following vector:

$$\left( +1, +\frac{1}{2}, +\frac{1}{3}, \ldots, +\frac{1}{N} \right),$$

and the total fitness $M_G$ for this state is given by the following:

$$M_G = \sum_{i=1}^{N} +1_i = +N.$$  \hspace{1cm} (4)

While every other state has a total fitness contribution that is between -$N$ and $N$. Thus all the network states with their fitness contributions can be represented in the form of an $N^*(L-1) = N^*(2-1)$= $D$ dimensional hypercube where each vertex represents a state or configuration of the network and the value assigned to the vertex is the fitness of the network in that state. Every configuration is one allele different than its neighbors in a $D$ dimensional hypercube. This hypercube is the simplest example of a fitness landscape, it has one minimum and one maximum and the rest of the fitness values are between -$N$ and
N. For example, if $N=4$ and $L=2$, then, the total number of combinations are $L^N = 2^4 = 16$. Table 1 shows each genotype and its total fitness contribution. Figure 3 shows the chart of fitness values against the genotype. It is clear from the fitness values that there are multiple genotypes for the same fitness value. Genotypes 2, 3, 5 and 9 all have fitness of -2, while genotypes 8, 12 and 15 have fitness of +2. There are 7 genotypes with zero fitness (4, 6, 7, 10, 11, 13, 14). Thus if we assign probabilities to each of these fitness values then it is clear that the genotype with zero fitness value has a higher probability of occurrence. And intuitively it makes sense that a genotype with all blocked links has a very small probability as does the genotype with all links in a free flow situation. Thus even a very simple coding scheme as given here gives a fairly good amount of information on the condition of a traffic network. This schema can be easily extended to a greater number of levels (alleles) to achieve a more realistic model of traffic flow conditions.

<table>
<thead>
<tr>
<th>Genotype</th>
<th>Fitness value</th>
<th>Total Fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>k=0</td>
<td>k=3</td>
</tr>
<tr>
<td>1=0,0,0,0</td>
<td>-1,-1,-1,-1</td>
<td>-4</td>
</tr>
<tr>
<td>2=0,0,1</td>
<td>-1,-1,-1,1</td>
<td>-2</td>
</tr>
<tr>
<td>3=0,1,0</td>
<td>-1,1,-1,-1</td>
<td>-2</td>
</tr>
<tr>
<td>4=0,0,1,1</td>
<td>-1,-1,1,1</td>
<td>+0</td>
</tr>
<tr>
<td>5=1,0,0,0</td>
<td>+1,-1,-1,-1</td>
<td>-2</td>
</tr>
<tr>
<td>6=0,1,0,1</td>
<td>-1,1,+1,-1</td>
<td>+0</td>
</tr>
<tr>
<td>7=0,1,1,0</td>
<td>-1,+1,-1,-1</td>
<td>+0</td>
</tr>
<tr>
<td>8=0,1,1,1</td>
<td>-1,+1,+1,+1</td>
<td>+2</td>
</tr>
<tr>
<td>9=1,0,0,0</td>
<td>+1,-1,-1,-1</td>
<td>-2</td>
</tr>
<tr>
<td>10=1,0,0,1</td>
<td>+1,-1,-1,1</td>
<td>+0</td>
</tr>
<tr>
<td>11=1,0,1,0</td>
<td>+1,-1,+1,-1</td>
<td>+0</td>
</tr>
<tr>
<td>12=1,0,1,1</td>
<td>+1,+1,+1,-1</td>
<td>+2</td>
</tr>
<tr>
<td>13=1,1,0,0</td>
<td>+1,+1,-1,-1</td>
<td>+2</td>
</tr>
<tr>
<td>14=1,1,0,1</td>
<td>+1,+1,-1,1</td>
<td>+2</td>
</tr>
<tr>
<td>15=1,1,1,0</td>
<td>+1,+1,+1,-1</td>
<td>+2</td>
</tr>
<tr>
<td>16=1,1,1,1</td>
<td>+1,+1,+1,+1</td>
<td>+4</td>
</tr>
</tbody>
</table>
2. K=N-1

Now, let us consider the case when each link interacts with all the other links of the network. Since, we do not yet know how each link affects the other links, let us assume that the complex interactions are multiplicative in nature, that is if links have high fitness values then the result of interaction would be a high fitness contribution value. On the other hand if one or more links has lower fitness values then the result of the interactions accordingly would reflect a low fitness contribution value. Another way to represent the interactions is to use a modified Tanner function (Tanner, 1961; Paelinck, Klaassen, 1979),

\[
\pi(f_i) = \frac{1}{K+1} \sum_{j=1}^{K+1} \pi(f_j) * (1 + d_{ij}) * \exp(-\alpha * d_{ij}),
\]

where, \(\alpha\) is a proportionality constant, \(d_{ij}\) is the distance (steps) between link i and link j, \(\pi(f_j)\) is the local fitness of link j, \(\pi(f_i)\) is the local fitness of link i and \(\pi(f_i')\) is the fitness potential of the link i for a genotype g; thus \(\pi(f_i')\) is a result of all the k+1 interactions between link i and other links carried out according to equation (5).
Note that the overall fitness level becomes smaller as the number of interactions increases from K=0 to K=3. This may be explained as a consequence of the conflicting nature of interactions among the genes which results in the reduced fitness maxima.

Figure 4: Hypercube Representation of Genotypes for Genes N = 4

<table>
<thead>
<tr>
<th>Gene</th>
<th>Genotype</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0000</td>
</tr>
<tr>
<td>2</td>
<td>0001</td>
</tr>
<tr>
<td>3</td>
<td>0010</td>
</tr>
<tr>
<td>4</td>
<td>0011</td>
</tr>
<tr>
<td>5</td>
<td>0100</td>
</tr>
<tr>
<td>6</td>
<td>0101</td>
</tr>
<tr>
<td>7</td>
<td>0110</td>
</tr>
<tr>
<td>8</td>
<td>0111</td>
</tr>
<tr>
<td>9</td>
<td>1000</td>
</tr>
<tr>
<td>10</td>
<td>1001</td>
</tr>
<tr>
<td>11</td>
<td>1010</td>
</tr>
<tr>
<td>12</td>
<td>1011</td>
</tr>
<tr>
<td>13</td>
<td>1100</td>
</tr>
<tr>
<td>14</td>
<td>1101</td>
</tr>
<tr>
<td>15</td>
<td>1110</td>
</tr>
<tr>
<td>16</td>
<td>1111</td>
</tr>
</tbody>
</table>

Figure 5: Fitness Landscape

In general, it may be said that as the value of K changes the fitness landscape also changes from a single maximum/single minimum fitness landscape to a rugged multiple max/min fitness landscape whose maxima and minima have reduced fitness values.

Let us assume that on average K links influence the traffic conditions on a link of the network. Further one may assume that the K links are spatially connected to the link,
i.e. they are neighboring links. Of course, this is not necessary, we could assume link effects once or twice removed. Thus K can have a value more than 0 but less than N-1. Then the total number of combinations that may affect a link for the 2 allele case (K and itself) is $2^{K+1}$. Again for L alleles of traffic flows, the total number of combinations is given by $L^{K+1}$. To create a fitness landscape for the entire network, one may use a random fitness function or some other function that reflects the general traffic conditions on the roads. In the later case the function could be a weighted combination of a number of traffic properties, such as peak flow times/numbers, density of the traffic, speed limits on the links or any other relevant property of the traffic on the road network. The specification of the NK transport model is complete when the assignment of the fitness vectors for all the links is finished. Once the fitness vector assignment is completed, the traffic flow landscape is represented as a hypercube in $N^{*}(2-1) = N$ dimensional space for 2 alleles traffic flow condition case and is represented as a hypercube in $N^{*}(L-1)$ dimensional space for L alleles traffic flow condition case. As was previously mentioned, each of the configurations (genotype) at vertex is one allele different from its D neighbors and accordingly its fitness is a little bit different than the rest of its D neighbors.

Now it is possible to make an estimate of the overall fitness of the road network for all genotypes using equation (6) as follows:

$$\Gamma = \frac{1}{L^N} \sum_{g=1}^{L^N} M_g$$

(7)

where $M_g$ is the fitness of genotype $g$. Equation (7) serves as the general fitness index of road networks.

Since the traffic flows on roads change dynamically, they do not lend themselves easily to modeling. One cannot associate a single equilibrium point at which the traffic flows settle down into a regular pattern. Instead, the traffic flows follow multi-equilibria metastable behavior, jumping from one configuration $g_a$ to the next configuration $g_b$ on the fitness landscape hypercube. The new configuration $g_b$ may or may not be in the
immediate neighborhood of $g_x$, the process of moving from this configuration to the next continues as the flow dynamics change on various links. Note that the movement over the fitness landscapes may not always result in better fit configuration. Consider a configuration $g_x$ from among all the other $L^N$ configurations, then it can be shown that, in general the probability that $g_x$ has a better fitness value than its $D$ neighbors is given by:

$$p(g_x) = \frac{1}{D+1}.$$  \hspace{1cm} (8)

The higher fitness value of configuration $g_x$ makes it a locally optimal configuration among its neighbors. Then for a landscape consisting of $L^N$ configurations, the total number of such local optima is given by:

$$E \approx \frac{L^N}{D+1}.$$  \hspace{1cm} (9)

Thus there exist a large number of locally optimal configurations for a traffic flow landscape. The local optima are the multiple equilibria that are scattered all over the traffic fitness landscape.

**Attractors and Attractor Basin**

Next, let us consider a simple road network consisting of $N=4$ links, namely 'a', 'b', 'c', 'd'; with $L=2$ alleles and $0 \leq K \leq 3$ interactions. Let us rank the 16 possible genotypes according to their fitness values. Let us assume that these links are segments of a road such that, during a time period $t$, the traffic on link 'a' moves on to link 'b' and so on. Let '0101' be the genotype representing the current traffic conditions on the four links. Then in one time period, as the traffic moves, the new genotype could one of the following, '1010,' the complement of previous genotype or '0000' all links congested or '1111,' all links are in free flow condition. None of these three successor genotypes are one mutant neighbors (just one of the links with a different flow condition) of the previous genotype. In fact the flow conditions on the successor genotypes could such
that the resulting genotypes are 2 or more but less than N mutant genotypes. Next let us consider a large network with N links. For such a network consisting of a large number of links, the successor genotypes could vary from being one mutant neighbor to N mutant neighbors. If the successor genotypes are same from one instant to another or if the successor genotypes change back into the original genotype then the original genotype becomes the attractor. In other words, if a set of different genotypes corresponding to small scale perturbations in the flows on links have the same successor genotype, then the members of the set form the so called attractor basin and the successor genotype may be designated as the attractor genotype or the so called metastable equilibrium genotype. On the other hand, if the successor genotypes are all wildly different then it is an indication that the traffic flow patterns are changing chaotically and that the network has become unstable. The changes in the genotypes from one instant to next can be measured in terms of the Hamming distance. Thus, the Hamming distance may serve as a measure of instability of a road network.

Search of Local Optima

If one could construct a traffic flow landscape at a given instant then in theory it is possible to estimate the time needed to reach an optimal solution. Suppose that a traffic landscape has been constructed and currently the entire network is represented as a genotype $g_x$ in this landscape. Next, an incident occurs on one of the links of the road network, the resulting traffic flow with congestion can be viewed as a configuration (genotype) $g_y$ on the same landscape and the amount of time needed for the network to reach from the current configuration (genotype) corresponding to the congested link, to one of the locally optimal equilibrium points is given by:

$$T_{opt} = \log_2 (D-1) - 1 \sum_{t=0}^{L^t} L^t$$  \hspace{1cm} (10)$$

where $D$ is the dimensionality of the traffic landscape, $L$ the number of alleles and $t$. The above result can be explained in terms of the rank ordering of the configurations.
(genotypes), the dimensionality of the landscape and self-avoiding biased random walks on the fitness landscape. As was mentioned earlier, for a $D = N(L-1)$ dimensional hypercube, a genotype at a vertex is at least one allele different than its $D$ other neighbors. Thus if we start at a worst fitness genotype, then moving to any of its neighboring $D$ vertices would lead us to a configuration (genotype) that has better fitness than the previous one. Since the total number of configurations is $L^N$, the rank order of the new configuration is between 2 and $L^N$. If one follows this in random fashion to move to a vertex that has better fitness than the previous one, then every such move makes the new configuration halfway closer to the remaining configurations. So as the improvement continues, the process slows down such that for every such move the time to search for a fitter neighbor doubles.

Yet another way to look at the ranked fitness landscape as an inverted fitness tree (see figure 6.) The inverted fitness tree consists of a root node (a) that corresponds to the worst fitness genotype, $g_w$, and the children or sibling nodes (b,c,...n) correspond to the other configurations or genotypes. At each level, there are $D$ nodes (dimension of the fitness hypercube corresponding to different configurations of traffic flows) that are one mutant neighbors of each other. These in turn have children at the next level and so on, till we reach the leaf nodes.

**Figure 6: Partial Fitness Tree of Genotypes**

```
Root with one of the bad fitness values
```

Level 0
```
          a
          |
         --
         b
         \
         c
         |
        ----
        d
        \
        e
```

Level 1
```
          a
          |
         --
         b
         \
         c
         |
        ----
        d
        \
        e
```

Level 2
```
          a
          |
         --
         b
         \
         c
         |
        ----
        d
        \
        e
```

Level 3
```
          a
          |
         --
         b
         \
         c
         |
        ----
        d
        \
        e
```
The leaf nodes do not have children. As we travel down from the root to one of the leaf nodes, the fitness of the genotypes increases, thus the root node has the worst fitness and the leaf nodes have better fitness, i.e., they represent one of the locally optimal fit genotypes (m) that have better traffic flows. It may be pointed out that the fitness tree need not always be such that the root represents the worst fitness. In fact for a genotype tree as described above, the root genotype may represent the current traffic flows on the links of the road network. If this is better fitness than its neighboring genotypes then the tree has just one node and that is the root as well as the leaf. On the other hand, we can search randomly for a better fitness genotype on one of the D branches of the root. Once such a genotype is found, then we are at the new genotype and repeat the process till we reach a local optimum. The total time or the number of levels of the tree becomes a measure of the time needed to reach a locally optimal genotype.

Any fitness tree constructed in the manner described above can also be transformed into a binary fitness tree (Horowitz, Sahni, 1985; Wilson, 1988) as shown in figure 7.

Figure 7: Partial Fitness Binary Tree of Genotypes

Binary trees lend themselves to analysis more easily than the random trees of the type shown in figure 6. As we move down from the root to either right or left child, we
prune our search for a better genotype by half. We can get an upper bound on the depth of a fully populated s node binary tree as follows. A binary tree with just one node has a depth of \( \log(1+1) = 1 \). For 3 nodes, the depth is given by \( \log(3+1) = 2 \), for 7 nodes the number of levels is given by \( \log(7+1) = 3 \). In general, for \( s \) nodes, the number of levels is given by \( p = \log(s+1) \). The depth \( p \) of a binary tree can be used as a measure of how far one must search for a local optimally fit genotype.

Similarly, we could use the techniques described so far to do the impact analysis on the basis of increasing (decreasing) the total number of links (N) or changing the value of \( K \) (the number of interactions per link) by generation of a genotype tree and searching for a locally optimal genotype that has a better fitness than the genotypes in its neighborhood.

Self Organization and Traffic Flows

As before we suppose that a traffic fitness landscape has been constructed for L alleles, N links and K interactions. Let us explore the self organizing properties of such a network. We rewrite equation (6) as follows:

\[
M_g = \sum_{i=1}^{N} \sum_{j=1}^{K+1} \pi_f (f_j) (1+d) \exp(-d_{ij})
\]

and from equation (7) we get the overall fitness of all genotypes for the network as follows:

\[
M = \sum_{g=1}^{N} M_g
\]

Then from equation (10) and (11) we can derive the probability of occurrence of a specific genotype, i.e.;
useful. Thus if we can reduce the uncertainty in information content of a system then we will have reduced the entropy of the systems and accordingly its internal fitness will have improved. Hence, if we have surveillance equipment to monitor the traffic flows (See figure 2) on all the links of a network then we have enough information to find the overall state of the network in terms of traffic flows. This reduces the uncertainty in the system since the state of the network system has given us the current genotype of the network and that means we know which vertex of the fitness landscape we are occupying currently. If this a good fitness vertex then it would be advisable to remain at that fitness level. On the other hand if the traffic network is on a bad fitness vertex, the TMC will have capacity to take measures to improve the fitness of the network and possibly evolve towards a region of better fitness on the fitness landscape.

One of the features of the traffic landscape is its relative independence of factors such as the fitness values and the number of alleles \( L \) (Kauffman, 1993). Since the traffic landscapes are mainly dependent on the values of \( N \) and \( K \), the TMC should be able to develop processes to maintain a level of service on the links of a network that would always give a better fit network configuration (genotype.)

In the next section we to apply the framework developed to the city of Fairfax. The traffic network consists of main roads and arterials as shown in figure number of links. The level of service concept from the Highway Capacity Manual (1985) can be used as the number of alleles \( L \) for each link on the roads.

THE TRAFFIC LANDSCAPE AND FAIRFAX CITY

City of Fairfax is an example of the phenomenon of the rise of the suburbs into business and employment centers. Figure 6, below shows the national capital region, the beltway and the emergence of multiple business/employment centers (Edge Cities, Garreau, 1991) in the national capital area. Fairfax city has experienced significant economic growth over last several years.
Accompanying this economic growth is a steady increase in the amount of traffic on the road network. A recent study in the city newsletter (The CityScene, Sept., 1995) estimates that the city roads handle four times (300,000 vehicles) the traffic normally generated by 20,000 residents. So where is all this traffic being generated? It is clear that the majority of these trips are generated by nonresident commuters who use the city road network to reach the employment centers. Many of its major roads, namely Rt. 123, Rt. 50/29 and Rt 236 serve as conduits for traffic that moves across the region to and from Washington D.C. and other suburban employment/business centers (See Figure 8 and 9). Since the city does not generate all of the traffic on the roads and with the given set of road networks, its main aim is to keep its major arterial routes clear of traffic congestion while ensuring efficient access for its residents to the road network.

Though, geographically the city is part of the National Capital Region and Washington Council of Governments area and is in the center of one of the fastest growing and wealthiest counties in the country, it is free by state statute to make its own traffic plans, independent of its neighbors. That means that the objectives of the regional, county and city may not be coincident. In fact the traffic plan and management strategies of the city may be in conflict with those of its neighbors.
We can use the N-K model to the city road network under different traffic flow conditions and determine the traffic flow index. Further, we can do impact analysis, by selectively blocking different sections of the roads and check how the flow index changes. Additionally, we can determine the number of sub-optimal equilibria traffic flow conditions that may exist for the traffic on these roads. It would be also possible to determine the amount of time needed to overcome the effect of incidents which would in turn help in incident management.

Another exercise would be to find out what would be the effect of adoption of a more regional traffic management strategy. This can be considered as alternate scenarios of traffic flow. We generate three traffic flow landscapes. The first one (LS1) consists of the road network of the city of Fairfax. The second landscape (LS2) consists of the road network of the city and the county. And the third (LS3) consists of the county road network without the city road network. These landscapes may be generated and the flow index calculated for each using variety of traffic flows, that is traffic flows during peak hours and off peak hours, traffic on work days and on holidays. Once the traffic flow landscapes are calibrated then the traffic flow indices (\( \Gamma \)) may be used to compare the traffic flows on day to day basis as well as to dependency and impact analysis.
CONCLUSION AND FUTURE DIRECTIONS

Defining fitness vectors for traffic flow on a road network creates a rugged fitness landscape. For large values of N (the number of links in a network) with K links (K < N) influencing each of N links generates a very complex traffic flow landscape. For K = 0, we get a simple traffic flow landscape with a single global optimum, in which all links of road networks are independent of each other. As the value of K increases, we get more complex traffic flow landscapes. The other extreme occurs when K = N-1. In this case each link influences flow of traffic on all other links. This type of landscape has an infinite number of local optima and is very rugged. The point is that the fitness landscape can be tuned from very smooth (K = 0) to extremely rugged (K = N-1) by varying the value of K. The traffic flow landscape model is primarily dependent on the values of N and K. The number of alleles and the distribution of the flows on these alleles does not have as much influence as N and K. Current and future study would involve the following:

1. Determination of ranking of the links according to the fitness criteria.
2. Determination of response times required to adjust to traffic incidents.
3. Creation of traffic flow landscapes for sub-networks of a large road network.
4. Application of the traffic landscape to the city of Fairfax.
5. Calibration of Fairfax city traffic landscape model.
6. Carrying out impact analysis for different scenarios of traffic flows.
7. Exploring the possibility of integrating the model with other dynamic traffic management models based on ITS technology.
8. To improve upon the fitness criteria that has been explained in Appendix A, to include the other qualitative factors mentioned in the Highway Capacity Manual (1985.)
References:


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The City Scene, Community Relations Office (September 1995), "A report to the Citizens of the City of Fairfax," City Govt., City of Fairfax, 25, 9.

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Appendix A:
Consider a road segment of length l and width w. Then the total area A of the road segment is given by:

\[ A = L^D \cdot W^D \]
or if we express w as fraction of l then
\[ A = L^D \cdot (\gamma \cdot L^D) \]
or alternately it may be expressed as follows:
\[ A = \gamma \cdot L^{2D} \]
(A1)

Equation (A1) can be re-written as:
\[ A \propto L^{2D} \]
(A2)

where D = 1, the dimension of the road segment. Now consider a stream of vehicles traveling on the segment of the road. Thus at any instant there are finite number of vehicles occupy a finite amount of space on a section of the road.

Since, the vehicles on a road are discrete objects and occupy finite and discrete amount of space, we can express the total area occupied by the vehicles as follows:
\[ a = n \cdot l^d \cdot w^d = n \cdot l^d \cdot (\delta \cdot l^d) \]
(A3)

where a is the average area occupied by a vehicle of average length l and average width w and \( \delta \) is a fractional measure for converting w into l. Equation (A3) may be expressed as:
\[ A = n \cdot \delta \cdot l^d \text{ or } A \propto (n \cdot l^d) \]
(A4)

Let us express the average value of vehicle length l in terms of the length of section of the road, then equation (A4) can be written as:
\[ A = n \cdot \delta \cdot l^d \text{ or } A \propto (n \cdot L^d) \]
(A5)

From equations (A2) and (A4) the density of vehicles occupancy \( \rho \) may be expressed as:
\[ \rho \propto \frac{n \cdot (\delta \cdot L)^{2d}}{L^{2D}} \text{ or } \rho \propto \frac{n \cdot \delta \cdot L^2}{L^{2D}} \]
(A6)

We can express the density function \( \rho \) by introducing a proportionality constant \( \beta \) in equation (A6) and get the following equation:
\[ \rho = \frac{\beta \cdot n \cdot \delta \cdot L^2}{L^{2D}} = (\text{const.}) \cdot L^{2(d-D)} \]
(A7)

Taking logarithm on both sides of equation (A7) gives us the following equation:
\[ \log(\rho) = \log(\text{const.}) + 2(d-D) \cdot \log L \]
(A7)

Since, D=1 we can get the following equation:
\[ d = \frac{\log(\rho) - \log(\text{const.}) + 2 \log(L)}{2 \cdot \log(L)} \]
(A8)

From equation (A8) we can get an expression for \( d \) as follows
\[ d = 1 + \frac{\log(\rho) - \log(\text{const.})}{2 \cdot \log(L)} \]
(A9)

It is clear from equation (A9) that value of \( d \) varies between a minimum of zero (free flow) and maximum = 1 (blocked link). Thus the actual value of \( d \) can be used as a measure of traffic of the level of service for assigning fitness values to sections of roads.