Role and Function of Gradient Induced Flows in Transportation and Social Networks

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1 Introduction

Transportation Systems are complex networks. The traditional means to describe complex networks is the random graph model (ER model) established in 1959 by Paul Erdos and Alfred Renyi (1959). The defining characteristics of ER random graph model are that they are statistically homogeneous and their degree (number of links attached to a node) distributions are poissonian (Albert, 2001). In contrast, recent empirical evidence shows real traffic and transport networks have a hetrogenous nature and their degree distribution has scale free power law distribution. Scale free characteristics of the transport networks suggest a small number of locations (nodes) within the network attract far more pepole and vehicles than others. It is thus reasonable to propose the observed scaling characteristics of the traffic flow in real traffic network is due to the nature of gradient fields which directs a large portion of traffic into locations such as shopping centers, house of worships and other important social and cultural infrastructures. In this paper we use the term 'node' to refer to any sites that a vehicle stops. Traffic red lights are nodes. Links are inter-connectors that allow one or more vehicles to travel between nodes. A Gradient induced flow (GIF) network or simply gradient network is then defined as the collection of all directed links within a traffic network (Toroczkai et al, 2004). GIF entities are of great practical importance in the fields of transport and urban planning as they offer far more efficient and robust transportation systems.

In this paper, we study the topological characteristics and functional properties of gradient networks. We define centrality measure in order to characterize GIF entities. We also develop a superstatistical model of urban traffic. We discuss the dynamical route toward global synchronization of our transport systems.

For clarity, we distinguish between the phase signal of traffic light (signal phase) and structural phase-state transitions (topological phase state). We refer to synchronizability as dynamical relationship between the nodes and not to some external dynamics.

1.1 Random graphs

Graphs are mathematical representation of transportation networks (Holmes, 2003). The simplest representation is static random graph of Erdos and Renyi. In this model, we start with N nodes and connect every pair of nodes with equal probability P, creating a graph in which links are distributed randomly. The random graph shows remarkable structural phase transitions. If for example, we increase the number of links (for a fixed number of nodes), all of sudden a single giant component appear in the network in which all nodes are fully connected. This is known as giant component of supercritical phase of random graph. The giant component of the supercritical phase of the random graph currently use by traffic engineers and urban planners to sample real traffic and transport networks. The problem with using random graphs as models for transportation networks is that it cannot account for the hetrogenous structure of scale free power law distribution observed in such networks. This is because all nodes are equally important in random networks. The degree distribution of random graph $\Pi_{static}(k = \deg ree)$, in the large N (=number of nodes) limit is a Poisson distribution.

$$\Pi_{static}(k) \approx e^{1/\langle k \rangle} \frac{\langle k \rangle^k}{k!} \tag{1}$$

where $\langle k \rangle$ denotes the average degree.

In summary, the basis of static random graph theory is based on assumptions that nodes are equivalent and links are distributed randomly. In practice, we assign weights to the links (costs) causing variation in the probability of connection between nodes. We can establish a gradient induced field by making the network weighted (Park et al, 2005). In the next section, we discuss the topological characteristics of GIF networks.

2 Topological characteristics of the gradient network

Gradient induced flow (GIF) networks or simply gradient networks (Toroczkai et al, 2004) have certain structural properties similar to power law scale free networks. Their degree distribution Π (K=degree) have scale free characteristics of the form:

$$\Pi\ (k) \sim k^{-\gamma} \tag{2}$$

where scaling exponent γ is a fine-tuning parameter which defines the dynamics of the network and its topological phase evolution. This form of the distribution is the easiest to see when the graph of probability distribution $\Pi\ (k)$ is plotted on the log-log scale. The slope of the line is the exponent γ of the power function.

GIF networks have a small world phenomenon and a high clustering coefficient. By small world phenomenon we mean that the average degree of separation or average shortest path between nodes is small. In urban traffic, the average shortest path length can be defined as the average minimum number of times vehicles need to stop (i.e. red traffic light, junctions, roundabouts and reversing) in order to get from one location (node) to any other location in the network (Mojarrabi, Gwal and Mojarrabi 2005).

Clustering coefficient of the GIF networks provide useful information about the community nested structure. The global clustering coefficient is average of all local clustering coefficients (Watts and Strogatz 1998). We can measure the global clustering coefficient ($C_{measured}$) in the traffic network by calculating the ratio of the total number of parked vehicles (N_{parked}) to the total number of available (possible) car parks (N_{vacant}) within the network (Mojarrabi and Mojarrabi 2005, Mojarrabi and Mojarrabi 2006):

$$c_{measured} = \frac{N_{parked}}{N_{vacant}} \tag{3}$$

The topology of the GIF networks also play an important role on their synchronization. For example, Li, Wang and Chen (2003) showed that they are robust but yet fragile in synchronization. This means they are robust against random node failure but vulnerable to the deliberate attack on their hubs (i.e. the nodes that lie on the tails of the distribution P(k)).

There is also an important engineering parameter called “betweenness centrality” B_i of the traffic node I_τ (red traffic signal, intersections, roundabouts) in traffic network. Here we define it as the number of the shortest path connecting two locations within the network that involve a stop at traffic node I_τ. It has been suggested by Hong et al (2004) that synchronization is enhanced if the betweenness centrality is reduced. The traffic node I_τ has an important functional role in the network as it sits between the shortest path connecting two locations within the network. This means it can be used to fine-tune the exponent γ by controling the traffic flow between corresponding locations. Betweenness centrality can be used to characterize GIF entities.

We classify GIF entities into two groups: firstly GIF entities with low betweenness centrality (i.e. local GIF entity) and secondly clear time scale GIF entities which have Maximum

Betweenness Centrality. In the next section, we details techniques to measure the topological characteristics of the GIF networks including an example. Gradient network is scale free network in which traffic jamming is limited compared to random graphs (Toroczkai and Bassler 2004; Park et al, 2005).

3 Measuring topological characteristics of gradient network

Scale free networks (SF) have been the subject of intensive research and scientific observation in recent years. A considerable number of real graphs in Biology, Sociology, Internet and telecommunications have scale free characteristics, i.e. the network looks the same when zooming in or out. NASA (Alexandrov 2004) has proposed scale free networks as their future air transportation systems.

There have been some attempts to infer scale free network characteristics within traffic network and urban network. Jiang and Claramunt (2005) provided the evidence that large urban street networks in the Swedish city of Gavle have small world characteristics but do not exhibit scale free characteristics. Yanguang and Yixing (2005) reported that urban systems and the road networks based on urban systems for cities of Hanan provenance in China are also scale-free networks. The real empirical data come from the city of Portland, Oregan, USA (Chowell et al, 2005), city of Marion in Adelaide, Australia (Mojarrabi and Mojarrabi, 2005), Beijing city in China (Wu et al, 2004) and Sardinia region in Italy (De Montis, 2006) providing the clear evidence the flows of peoples and vehicles within the transportation networks have power law scale free characteristics. Here, we review of the results obtained from the Marion shopping center in Adelaide to show the first evidence of the existance of a local GIF entitiy in traffic network.

To explore whether the network around the shopping centre was scale free, Mojarrabi and mojarrabi (2005) created the statistical profile of the degree distribution. They considered nodes to be any sites, at which a vehicle stops or parks. For example, a parked vehicle within the physical boundary of a house was treated as a node with degree 1. Similarly nodes with degree 2 were sites in which two vehicles stop within the physical boundaries of the site and so on. The number of vehicles that had stopped for the red signal of traffic lights was counted as its node degree.

In this way, they created a cumulative network consisting of about N=3445 sites with the mean degree of $\langle k \rangle = 11.8$. The degree distribution had scale free characteristics with scaling exponent $\gamma = 1.1 \pm 0.3$. The distribution also showed an unexpected characteristic dip at degree 2 and exponential cut-off at degree 250, presumably due to the limitation in the car park capacity arising from city planning regulations (Figure 1).

They used the linear fit of the first nine points to calculate the error in the exponent of the power law as they contain most of the data and were less affected by error distortion of log-log transformation of the tail (Goldstein, Morris and Yen, 2004).

The other characteristics of the scale free networks such as high clustering and small world phenomena were also measured. The clustering coefficient was found to be $C_{measured}$ = 0.56 ± 0.04 far larger (164 times larger) than corresponding clustering coefficient calculated for random graph C_{rand} = 0.0034.

The network around Marion shopping centre had an average short path of about, L = 3.2, which was small compared to the size of network.

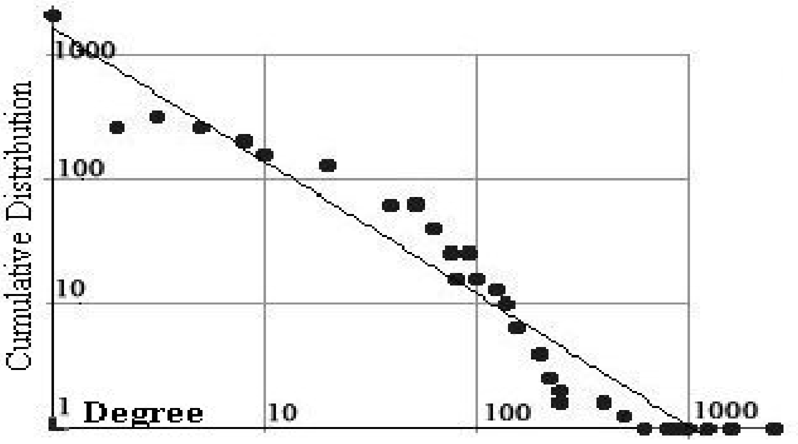

Figure 1 Degree distribution of the traffic network around the vicinity of Marion Shopping centre. The log-log plot of the cumulative distribution of the graph shows a power law distribution with $\gamma = 1.1 \pm 0.3$. The distribution has a characteristic dip at degree 2 and a cut-off at degree 250.

4 Gradient network modelling

4.1 Background

To date, two potential theories have been put forward to explain the observed Gradient Induced scale free behaviour of the real traffic networks.

In the first model, Mojarrabi and Vogiatzias (2005) proposed that the origin of this class of network within urban traffic is due to the competitive nature of the nodes at the microscale level. Nodes compete to attract vehicles. As the flow rate increases (more vehicles enter the network) the model predicts the existence of Fit-get Rich and Bose-Einstein condensation as a result of a fitness mechanisam. They then use the phase-state diagram of evolving scale free network to create the optimised solution for the end to end delay in the context of a strategy and tactical construct theory called Locality-Scope (Vogiatzis, 2005). In this framework, the scope provides the external synchronisation and optimisation services of the traffic lights using Nash flows. Section 4.2 contains detailed discussion about this model.

This model is, however, inedequate to account for all real traffic situations. In fact, there are situations within the traffic network that fitness of the nodes may vary due to events such as collisions, accidents, traffic jams and/or other types of spatial chaos or even due to some external influence such as abrupt weather changes.

A further problem is the fact that the model uses the ingredieants of preferential attachment. It assumes new vehicles tend to attract to the nodes that are already established and attaractive. This imply that the new vehicles joining the network must have some prior knowledge of the attractiveness of locations within the local area in order to choose with whom to join. This is certainly not always the case. A similar view was expressed by Servedio and Caldarrelli (2004).

In addition, the model does not include the internal synchronisation of the traffic light network on different time scales, from microscale at the very early stage of formation of gradient flow up to the macroscale at the end of time evolution of the gradient network.

Mojarrabi and Mojarrabi (2005) then proposed a superstatistical approach to traffic network around large shopping centers. In this model, a two-folded process is responsible for the emergence of scale free power law structure within the traffic network: a gradient induced flow resulting from the competitive dynamics of the nodes, and secondly, the temperature fluctuation associated with varying probability of connection of the nodes due to events such as collisions, accidents and traffic jamming (spatial chaos in the background). They established the joint probability of these two processes are scale free network with adaptive phase evolution.

Although it is reasonable to assume in a great number of cases that the emergence of gradient network is due to competitive nature of the nodes, this is certainly not always the case. For example, A GIF network can be formed due to cooperation/partnership or mutual participation between the nodes. As an example, we can imagine the traffic flow around the vinicnity of the Gleneg beach in Adelaide or Taj Mahal in India is a result of inherent beauty of these places. It is pluasiable, a subsatantial number of large hotels and commercial developemnts will gain benefit from the proxity to these centers of attraction. Another example with inherent attraction properties are religious infrastructures that often ilicit a deep feeling of peace, strengh and fellowship in their worshipers.

In general, the hetrogenous relationship between nodes and the emergence of gradient induced flows are not necessary due to one factor, but a combination of many factors. If this is the case, then it is pluasable, our model will not identify all relevent micro-macro linkages of the mesoscopic level suggesting anomalous results (White et al, 2004) . i.e. We can not account for all the functional and relational abilities of the multicommuniy structure of the network when each community has its own GIF's. When placed in the context of globalization, this may prove crucial to operationalize a stable and roubust global integrated transportation system that serves to secure a sustainable human future (IRG SCAFT 2006).

In this paper we show, for a suitable superstatistical model, the main dynamical path toward global synchronisation within our increasingly close-knit "global village" is oriented toward clear time scale GIF entities, persumably, those of religious communities. Here, we will focus our attention to the role and function of clear time scale GIF superstructures such as House of worships to the design and planning of a futuristic global integrated transport and urban system.

Here we propose the evolution of traffic networks around large shopping centers and religious infrastructures as gradient flow with respect to an innate quality called "energy" ε_i and a fluctuating parameter *T*, called temperature refereeing to the variation in the probability of the connection between the nodes due to temporal chaos in the background. Since synchronization is related to the topological scales of the gradient field, then it is possible to observe the gradient network with temperature fluctuation as a type of evolving scale free network constrained both in its direction and in its form.

4.2 A preferential attachment and fitness model of traffic network

In an evolving traffic network the probability Π that a certain vehicles parks at certain node *i* is given by:

$$\Pi(\kappa_i) = A_i + a_i k_i \qquad (4)$$

where *A* is the physical space that originally attracts a vehicle.

Once a vehicle stops within the physical space, then the second mechanism $a_i k_i$ starts. Vehicles prefer to join the sites that are more attractive and established. Scale free properties emerge as a result of this mechanism. The parameter a_i is the rate of the growth of this mechanism. It will determine the value of the exponent γ of the scale free power function. k_i is the degree of the node *i*.

In real traffic networks, sites have limited capacities to attract more vehicles; for example, after some time, the car park may become full, however there are still other mechanisms to consider in the evolution of the network.

The sites where vehicles stop have an intrinsic tendency to increase their degree at the expense of the other nodes. The competition is costly and must be done in the time scale of the dynamics of the traffic network. Bianoconi and Barabasi (2001) proposed a fitness mechanism in which each new node has a different fitness η. In traffic networks, the 'fitness' is the ability of the node to pay the cost in order to succeed in accruing new links in a competitive environment. Each node employs tactics to minimize the link cost or equivalently its average time delay payments. As a result of this fitness mechanism, the newly arrived node may win over old established nodes.

Under these conditions the equation 4 becomes:

$$\Pi(k_i) = A_i + a_i K_i + \frac{\eta_i k_i}{\sum_j \eta_j k_j} \qquad (5)$$

where $\eta_i = e^{-\beta \varepsilon_i}$ is the fitness of the node *i*. The energy ε_i is the ability of the node *i* to retain its competitiveness and $\beta = \frac{1}{T}$ plays the role of inverse temperature T. We can use it as a control tuning parameter. Furthermore the denominator normalizes the distribution and the sum is over all nodes *j* present within the network. The rate of change of the degree of the node *i* (i.e. the rate at which particles accumulate on energy level ε_i) is given by:

$$\frac{\partial k_i}{\partial t} = m \frac{\eta_i k_i}{\sum_j \eta_j k_j} \qquad (6)$$

where *m* is the number of links that a new node has when it joins the network.
In the limit of $t \to \infty$, the evolving network maps into a Bose gas as shown in figure 2(a).

Bosons are identical particles which can share their quantum states. Photons and Helium-4 atoms are bosons. The fact that particles can be identical has important consequences in statistical mechanics calculations as a result of probabilistic laws. The statistical behaviour of the bosons can be determined from the so-called Bose-Einstein Statistics.

In this paper, we show that the mathematics of the atomic boson is similar to the mathematics of the traffic around large shopping centers.

We can treat the links within the transport networks as identical particles. Vehicles are allowed to park in any of parking sites. This will allow us to represent entire transport system as a Bosanic network. Nodes can be represented by energy levels and links are represented by particles in energy levels.

The mapping indicates two distinct phase evolutions in the evolution of the traffic network.

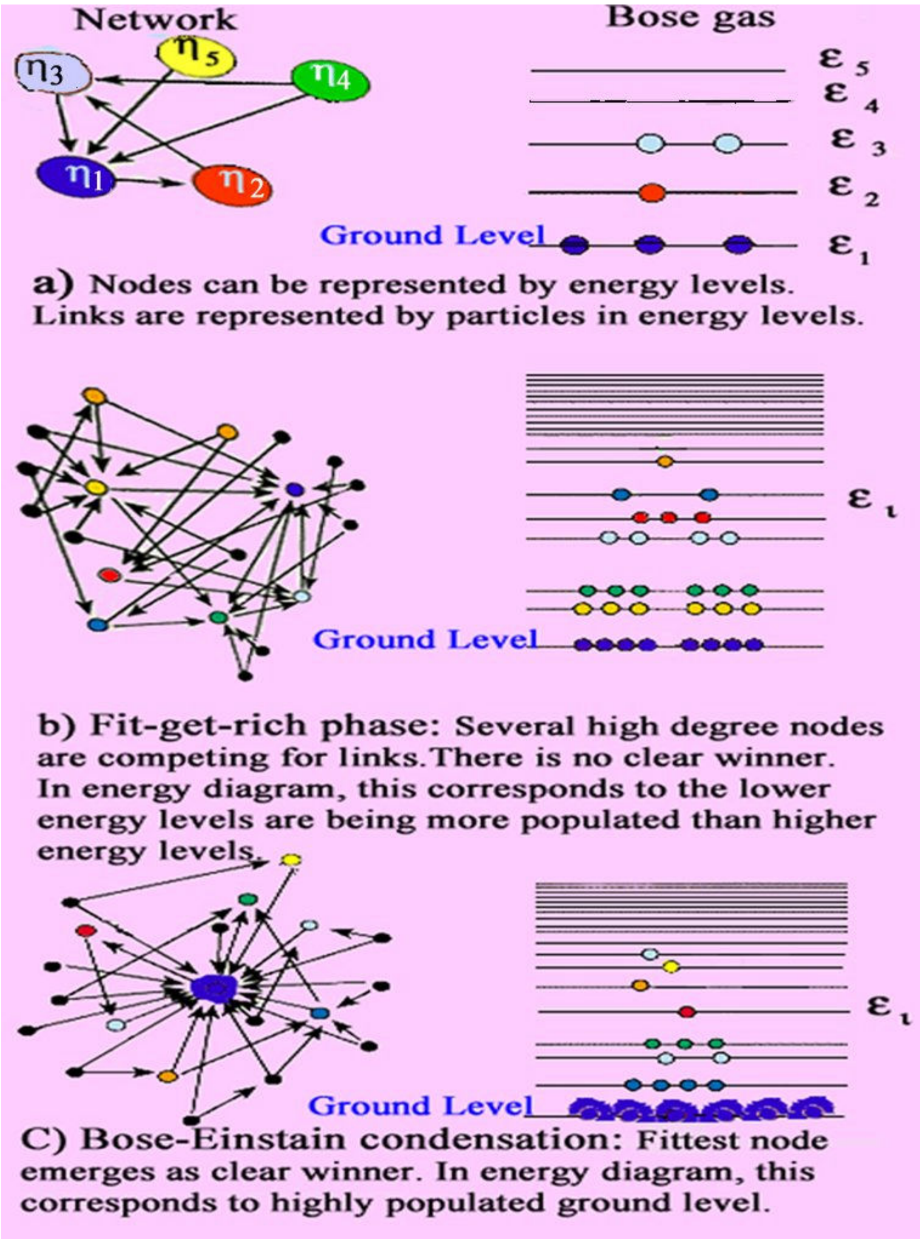

Figure 2 A schematic illustration of the mapping between the scale-free model with fitness η and a Bose gas (Barabasi, 2001).

From the figure, one can see the fit-get–rich phase (FGR) in which several high degree nodes accompanied by many less connected nodes exhibit the power distribution relationship $k^{-\gamma_{FGR}}$. The difference in value of the exponent from the scale free status to FGR indicates the dynamics of the system has been shifted from established nodes to that of fittest nodes. In the energy diagram of figure 2b, the FGR phase characterized by a few highly populated low energy levels.

In Bose-Einstein condensation, the winner takes a finite fraction of all links. In the energy diagram this corresponds to the most populated ground level and sparsely populated higher energy levels (Figure 2c); it occurs at the critical temperature T_{BE}. The difference between FGR and BEC is in the relative occupation number of the large nodes at different temperatures.

Real traffic networks are however directed networks in which the traffic flows have an incoming and outgoing direction. In this case, we consider the network as two isolated incoming and outgoing subsystems.

The mapping of directed traffic networks can be done independently for each subsystem as shown in Ergün and Rodgers (2001) and Sotolongo-Costa and Rodgers (2003). For each node (site/ sites in which a vehicle stops) we assign 2 'fitnesses' (incoming fitness η_{in} for the receiving node and outgoing fitness η_{out} for the emitter node). This means that the link can be grouped into two different separate subsystems in which each group can separately map to Bose gas similar to figure 2. Under this condition, the creation of a directed link corresponds to the creation of two particles, one in each subsystem, simultaneously. In the mapping, the fittest node (high η) results in the lowest energy levels (energy ε). A link from node *i* to node *j* in the network corresponds to creation of a particle in level ε in the Bose gas for each subsystem. The network evolves over time by adding a new node. The super node appears as a highly populated, lowest energy level while higher energies remain only sparsely populated.

The solutions show similar phase-state transitions of FGR and Bose condensation phases for each isolated subsystems as that of undirected network. However T_{BE} may be different for each subsystem.

4.3 Superstatistical model of traffic network

We start with a short introduction to the "superstatistics" concept itself. Superstatistics or statistics of the statistics is the model developed by Beck and Cohen (2003), Beck (2004), Sattin (2005) and (Beck, Cohen and Swinney, 2005) to describe the inhomogeneous non-equilibrium systems. These systems usually have different dynamics on different time scales. Superstatistics allow us to postulate a universal statistical profile for such systems. For example, we can view a traffic network as a non-equilibrium system in which a number of vehicle move randomly (i.e. A poission distribution for reasonably large number of vehicles) through a gradient field with energy ε_i. There is also a second much slower dynamics of the background, namely, the spatiotemporal fluctuation T of the background. For example, Drivers make mistakes and collisions may happen or traffic jams may occur. The net result of these fluctuations is to cause variation in nodal fitness and thereby varying the probability of connection. Nowadays varying fitness is referred to as hidden variable theory in literature (Servdio and Caldarelli 2004). I.e. we have a fluctuation random graph with distribution $\Pi(T)$ instead of a static random graph with distribution $\Pi_{static}(k)$. In this paper we show the poissonian transformation of $\Pi(T)$ is power law scale free.

The probability distribution for static random graph $\Pi_{static}(k)$ is a poissonian of the form:

$$\Pi_{static}(k) \approx \frac{T^k}{K!} e^{\frac{1}{T}} \tag{7}$$

where average degree $\langle k \rangle$ in equation 1 corresponds to temperature in equation 7. The question we need to answer is what the form of degree distribution $\Pi(k_i)$ is when $\langle k \rangle$ is a stochastic variable. In this case, the distribution in equation of 7 is a conditional probability $\Pi(k_i \mid T)$. i.e. the probability of finding a certain number of vehicles attracted to a node i given some value of Temperature T.

However, we are interested in the degree distribution $\Pi(k_i)$ of a fluctuating random graph which is the probability to observe a certain number of vehicles attracted to a node i irrespective of the T. We propose that the degree distribution $\Pi(k_i)$ can be found from marginal of the joint probability $\Pi(k_i, T)$ using the superstatistics tools developed in the papers Abe and Thurner (2005) and Beck (2004). The joint probability $\Pi(k_i, T)$ is simply the probability to observe both processes for a given value of *K* and *T*. i.e.

$$\Pi(k_i, T) = \Pi(T)\Pi(k_i \mid T) \tag{8}$$

Finally from equations 7 and 8 we deduce:

$$\Pi(k_i) = \int_0^\infty \Pi(T)\frac{T^k}{K!}e^{\frac{1}{T}}dT \tag{9}$$

that means the degree distribution of $\Pi(k_i)$ can be found from the superposition of random graphs $\Pi(T)$ and $\Pi_{static}(k)$ in the form equation 9. Abe and Thurner (2005) have established the form $\Pi(k_i)$ is a power law scale free distribution using the example of a quantum mechanical harmonic oscillator.

Here we offer a simpler approach for the gradient field defined to be the number of possible fittest nodes that vehicles may be attracted within each traffic light phase. The gradient network is then defined as the collection of all directed links attracted to the fittest nodes or supernodes.

We follow a similar approach as in the paper by Argentini (2005). The flow on a node *i* at a given traffic signal phase $S_{i+\Delta t}$ depends on the flow at signal phase S_i with the probability $\Pi(k_i)$ given by:

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j} \tag{10}$$

where k_i is the degree of the node *i* .The flow rate at which vehicles accumulate on node *i* is given by Albert and Barabasi (2002) continuum approach similar to equation 6 (see section 4.2).

$$\frac{\partial k_i}{\partial t} = m' \frac{\eta_i' k_i}{\sum_j \eta_j' k_j} \tag{11}$$

where η_i' is defined as the fitness of the node *i* to stay with the flow and m' is a function that relates to the general properties of the field in the node *i* to the temperature fluctuation within each traffic signal phase S. Numerically it is related to the road and flow parameters such as the number of lanes, the speed, viscosity and density of the flow. It can couple to a transport equation through the energy ε_i. Here we assume m' is a constant referring only to the geometrical parameter of the parking sites in which a vehicle has been attracted.

The intrinsic fitness η_i' is generally a power law distributed function (Cladarelli et al, 2002) which couples field energy ε_i with background temperature T. Here we choose $\eta_i' = e^{-\frac{\varepsilon_i}{T}}$ which a simple way is for supernode to pumps its field energy into the system. Under these conditions the equation 11 has similar form as equation 6. i.e we have shown the poissonian transformation of $\Pi(T)$ is power law scale free. It is evident that the origin of this power law is statistical and therefore is different from the origin of GIF networks. However, we can still observe gradient network scale free structural characteristics even when spatiotemporal properties of the background is embedded into the dynamics of the system. However, the synchronization dynamics of the network would be altered from the original optimal design.

In the next section, we investigate the tempral dynamical attributes of the gradient network when placed in the context of synchronization (considering spatiotemporal fluctuation T of the background). Later in this paper, synchronization will be put forward as a mechanism to frame how different transportation/ urban systems distributed across the globe can be integrated in a sustainable manner.

5 Synchronization

It is suggested by Arenas, Diaz-Guilera and Perez-Vicente (2006) and IRG SCAFT (2006) that often the neigbours of the fittest node cooperate to form local clusters. These synchronized clusters will grow in size as more nodes join the flow creating larger and larger community structures up to the final stage when the entire population has synchronised their phase. This process will occur in a clear time scale from the microscale at very early stage up to the macroscale at the end of time evolution. We use popular Kuramoto model (Kuramoto and Nishikawa, 1987) to investigate the synchronisation nature of this process in gradient network.

$$\frac{d\Phi}{dt} = \omega_i + \sum_{i_{neigbours}} W_{ij} \sin(\Phi_i - \Phi_j) \qquad (12)$$

here ω_i and Φ_i are the original frequency and phase of the individual oscilator.

W_{ij} is the weight parameter of the gradient network. It depends on the fitness of nodes i to …N. The gradient network interacts with the background fluctuation field parameterized by T within a time step Δt_h. In general Δt_h is the fraction of time the fluctuation background spends in a certain state. For example an accident might take more than one traffic phase Δt to clear by re-routing the traffic. The effective weight parameter $\overline{W_{ij}}$ of the gradient network is then the weighted sum of all W_{ij} spent interacting with background. The effective weight $\overline{W_{ij}}$ causes a shift in the field distribution. As time passes, the field distribution will be shifted to a degree that is not centered at origin anymore. In this case the transition cycle of the traffic lights cannot be completed on time as different topology implies different values of tuning parameter γ. A possible solution is to reset the system defaults by for example re-zoning. To understand this correspondence we need to look into the Laplacian matrix form of the equation 12. From the eigenvalues obtained from the solution of the Laplacian matrix equation, we can see gaps which correspond to the times of resets often suggesting the emergence of new community structures with different functional time scales. In this way we conjecture that the eigenvalue solutions to the Laplacian matrix contain the synchronization codes for the traffic lights.

The point to be stressed is that now equation 12 can be written as

$$\frac{d\Phi}{dt} = \omega_i + \sum_{i_{neigbours}} \overline{W}_{ij} \sin(\Phi_i - \Phi_j) \qquad (13)$$

this means we can always create a local gradient network easily fitted to synchronize by making the network weighted using the methods of superstatistics. This proposition has been supported also by Park et al (2005).

Putting these arguments together, although many experts employ successful theories of traffic flow in the local network, such models altogether miss the point that traffic network can have scale free characteristics. The idea that structures emerge within traffic gradient fields (and social fields as well) is an important consideration with regard to prior identification of the community structures essential for the establishment of dynamical route toward global synchronization of often our disjoined world transport network. Naturally, the first thing is to look for a benchmark. It is plausible we initially look for an established community structure which has a well detectable synchronization codes to serve as our benchmark.

What we are looking at is a community structure that has evolved from the embryonic stage up to the macroscale at the end of time evolution showing non-trivial topological structures with multiple time scale for synchronization. For this reason the method of community structure benchmarking algorithm develop by (Arenas, Diaz-Guilera and Perez-Vicente 2006; Nel and Serfontein 2005 and White et al, 2004) stand out as a natural choice for our study. An outcome of these studies is that the networks that have a nested multi-community structures with an overall clear time scale GIF topology, presumably those of religious communities and multinational organizations, provides the best dynamical route to global integration of our transport networks.

There are several criteria for the Clear time scale GIF entities to be accepted as a benchmark following the line of White et al (2004). Firstly their synchronisation code should show adaptive patterns over time; secondly their fields should embrace the entire network and actively support collaboration among the nodes. Using the terminology of White et al (2004), synchronization acts in the gradient induced fields "as a radar screen for searching for prospective partners" "a ladder for successful attachments, and a "source for collaborative resources".

In terms of mathematical relations, it is equivalent to say that the eigenvalue gap for the Laplacian matrix of the chosen organization should enable synchronization for a wide range of engineering parameters and also in the presence of transportation and logistical delays. Since eigenvalue gaps within the social networks are corresponds to the periods of community structural developments, the supra social organization that successfully have transmitted these codes to significantly diverse geographic units of the planet bear distinctive imprints of being clear time scale GIF entity and a formal benchmark candidate. Not unlike IRG SCAFT (2006), we are proposing that the combined synchronisation codes of religion social network spectrums show a clear time scale gap offering a dynamical route toward global integrated transport and urban network.

The key to this finding is the design planning of Baha'i House of worships offering a universal outward expression. In addition to the temple, they have a travel and urban centre in one location catering for all social, educational and cultural needs of communities. In this way they transfer their own established dynamical route to all other organizations in which certain microscopic behaviour and local community structure order is required before they can be linked organically to the macro structures of the global integrated gradient network. We also point to the evidence that House of worships have an inherent feedback loop design to prevent single organizational monopolies over the entire time scales. For this reasons, we believe they can serve as a benchmark for creating global integration transportation / urban systems.

6 Conclusion

The interplay between theoretical studies and empirical observation of scale free nature of human mobility has led us to design new tools and techniques which will revolutionalize our understanding of the nature of globalisation forces. Superstatistics offer transport and urban planners with excellent tools to extract more information hidden in the wiring of social and transport network. For example, using methods of superstatistics we have been able to show synchronisation code of religion infrastructures favour gradient field interactions and thereby a global integrated transportation/ urban system is woven into their clear time scale gradient induced infrastructures.

We believe that these results can serve as a starting point for the developmet of an economically feasible and robust global integrtaed tarnsportation system that serve to secure a sustainable human future.

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