

On Identifying Dynamic Intersections in Large Cities

Jordan Ivanchev¹, Heiko Aydt², Alois Knoll³

Abstract—As the complexity of traffic conditions in large cities increases it becomes important and highly desirable to be able to analyse the spatial and temporal nature of such systems. Due to the heterogeneity of traffic demand and road network topology [1], it is possible to find “hot spots” in a network that present a challenge for city planning and conventional intersection control methods. This paper presents an approach to identify such places as physical intersections in a traffic network with dynamically changing demand conditions in time and to quantify the level of volatility at those locations. We design a model that is used to simulate commuters path choices using a stochastic routing approach. We perform a case study for the city of Singapore and calibrate our model with national survey data describing the travel habits of the population. The results from our simulation are used to analyse the traffic conditions in the city. We are able to identify and study highly dynamic intersections and observe that such locations in fact exist and contribute to the heterogeneous dynamic profile of the road network.

I. INTRODUCTION

IDENTIFYING “hot spots” in a complex network is a problem that is of great interest to engineers and researchers. The analysis of such locations is used in order to gain a deeper understanding of the system’s dynamics and to possibly control it. In the case of transportation systems, dynamically changing parts of the network present challenges to city planners and force them to find various solutions for their optimal control by planning new infrastructure developments [2], control strategies [3], novel policies [4], etc. When looking for special locations in transportation networks one has to choose whether to examine the roads (edges) or intersections (nodes). The intersections are actually the places where drivers make choices, and what is sensed at the roads are just the consequences of those choices. Therefore, instead of examining roads, a more topologically central approach would be to examine intersections instead.

Intersections in cities are usually controlled by traffic lights. Cities that exhibit high traffic demands also may employ smart traffic lights [5], that adapt in real time to changes in the traffic system are being integrated in modern cities in order to optimise the flow of traffic. As there are many discussed strategies for traffic light control, there is a fundamental element that is not present. How can we find the locations where those smart traffic lights should be installed? The installation costs of such

type of technology are not negligible and therefore it is not advisable just to install one at every intersection. Moreover, some intersections exhibit very static behaviour throughout the day and for them a static frequency controlled traffic light system can be sufficient. There is, however, a need of a method that is able to point out to the intersection that have the biggest demand for adaptive control due to their unpredictable and constantly changing dynamics.

When a traffic light signal pattern is being optimised the traffic demand throughout the day is taken into account and the best possible timings of the signals are chosen. It is important to note, however, that the traffic demand may change abruptly. For example between morning and evening rush hours the migration patterns of the commuters are qualitatively different, going from the residential areas to the business and industrial areas in the early part of the day and returning after work. In this case a universal timing solution might just be inapplicable and even lead to further congestion as shown in Fig. 1. It is not necessary that the dynamics of the intersection have a bimodal nature due to morning and evening conditions. It might be the case that even higher degrees of variations and abrupt changes in the drivers demands at an intersection occur throughout the whole day as a result of the complexity of the system.

Even if there is a successfully implemented dynamic control over the flow of vehicles, the varying volumes of cars taking different turns at the intersections will demand a changing capacity of the respective roads. The number of lanes and therefore the capacity of roads is, however, rather fixed. Consequentially, the number of lanes must also be optimized according to the traffic demand. If the worst case scenario is always considered, the roads will be planned with too many lanes and space will be not utilised during most of the time. Moreover, the construction of such broad roads might not be possible at all times. If the average case is considered (daily optimal), due to the extreme variability of the intersection, at some point the flow will have a radically higher value than the capacity of the road. This may further create an avalanche of congestions that can spread throughout the whole network.

In summary, such types of intersection can hardly be resolved by traffic lights and proper road width planning and seem like a source of imminent problems. It is, therefore, desirable that such locations are to be avoided in the first place by careful road structure planning. The existence of such highly dynamic intersections implies an improper combination of traffic demand and network topology. Of course, there are other ways to fix such locations if they already exist by either using traffic lights at other intersections to redirect flows or construction of new roads in order to relax the variability.

¹TUM CREATE, 1 CREATE Way, 10-02 CREATE Tower, Singapore 138602 jordan.ivanchev@tum-create.edu.sg

²TUM CREATE, 1 CREATE Way, 10-02 CREATE Tower, Singapore 138602 heiko.aydt@tum-create.edu.sg

³Technische Universität München (TUM), Institute for Informatics, Robotics and Embedded Systems, Germany knoll@in.tum.de

When dealing with complex networks and systems it is always better to consider the whole system rather than to look at specific locations in it. Fixing or optimising one intersection with dynamic behaviour might create another one at a distant intersection due to the high degree of interconnectedness in traffic networks. Therefore evaluating the dynamic profile of all network intersections and comparing it to this of other networks can give precious inside about their dynamics. Volatility and very dynamic and rapid changes in traffic demand at intersections makes their control challenging. Therefore, it is desirable to have less such intersection in a city in order to reduce congestion. In this line of thought, the level of such dynamics can be used as a optimisation heuristic that needs to be minimised so that the traffic itself is improved.

In a more fundamental aspect, traffic is determined by two factors: traffic demand and transportation network topology. The existing measures governed mostly by the demand are link flow, link average speed, etc. Measures connected to the topology are centrality, heterogeneity, entropy, etc. There have been previous efforts to define entropy of a node or a link but only in a purely topological sense [6]. We strongly believe in the need of employing the information contained in the OD matrix as well in order to come up with a more useful analysis measures of traffic networks. In this study we define the dynamic factor of a node using both information about the traffic demand and topological information about the network.

The main contributions of this work are:

- Definition of the dynamic factor measure for a node in a traffic network used to identify dynamic intersections.
- Definition of the dynamic factor of a network in order to compare it to other networks.
- Stochastic routing modelling and calibration of path choices.
- Case study for a realistic scenario for the city of Singapore.
- Analysis and discussion of heterogeneity of dynamic factor measures for a real world system.

II. LITERATURE REVIEW

Intersections that experience a large amount of traffic have been studied widely in literature. They are typically called “critical intersections” [7] and [8] and the critical traffic volume through the has been defined in [9] and further modelled in [10] using queue dynamics and in [11] for unsignalised intersections. The characteristics of critical intersections has also been an object of statistical analysis in [12], where data from various congested intersections in Shanghai during peak hour is processed and analysed. The study shows that the characteristics of intersections varies evidently from site to site.

Modelling traffic volumes in a city, which directly determines flows at intersections, has been performed in [13] by using a gaussian mixtures approach. One of the crucial factors that determines the performance of a network is how much the traffic demand on it varies in time. In [14] the variations of traffic on a daily and weekly scale are examined using cluster analysis techniques.

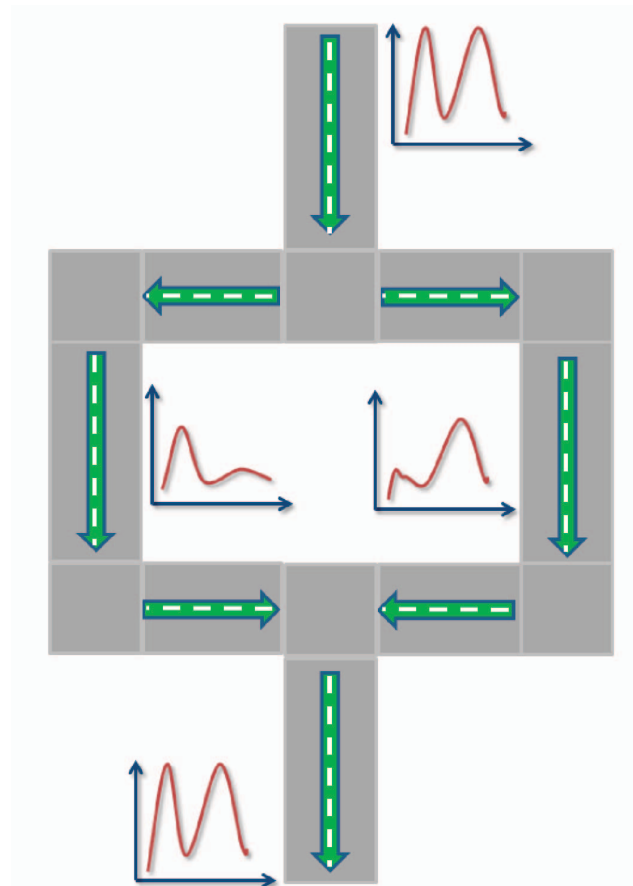


Fig. 1: Diagram describing a simplistic example of change in demand depending on the time of day. Next to the roads we can see the flow vs time chart. It can be observed that during the morning, most of the agents make a right turn, while in the evening most of the agents would make a left turn. This creates a dynamic intersection that experiences varying traffic demand throughout the day. As we can see after the roads merge again there is no variation. A static optimal control strategy would be to have equal amount of cars go to the left and to the right throughout the whole day. In this case congestions will occur for the cars making a right turn in the morning and a left turn in the evening.

The criticality of a road can also be defined using the network robustness index based on link flows, capacity and topology [15] or by identifying the most used link among all shortest paths computed on a graph as in [16]. While in [17] the importance of roads is simply defined to be proportional to the traffic load on them, in [18] three measures of centrality for a street are suggested: closeness, betweenness and straightness and their correlation to various economic activities in the respective areas are examined. Another study that uses a combination of factors to determine the criticality of a link is [19] where road criticality can be defined as a combination of three factors: road flow and capacity, which looks at V/C

ratio, path level, examining estimation of path travel time, and on a network level, looking at the percentage of OD pairs that use this road.

Measures of entropy are also used in literature in order to study the topological structure of networks such as in [20] where existing measures of heterogeneity, connectivity, accessibility, and interconnectivity are reviewed and three supplemental measures are proposed, including measures of entropy, connection patterns, and continuity. Furthermore, in [6] a family of graph measures used in various fields based on entropy are summarised.

In order to be able to plan or simulate an intersection one also has to evaluate the turning probabilities of the traffic participants. This has been done in [21], where using those probabilities a road density prediction method is described. It should be noted that most methods found in literature are concerned with analysing and simulating intersections for rush hour conditions, while neglecting the temporal nature of traffic, the change that the flows might exhibit throughout the day and their effects.

Moreover, the network itself can have some properties that are usually based on the structure of the system and not on local properties of its elements. In [22] the development of the Swiss road and railway network during the second half of the 20-th century is investigated. It is observed that the spatial structure of transportation networks is very specific, which makes it hard to analyse using methods developed for complex networks.

As road networks are subject to evolution, when societies change and cities grow the traffic demands and the road network itself changes with a high degree of self-organization and spontaneous organization of hierarchies. This phenomenon observed in [23] leads to imperfections of the once planned infrastructure. Long term temporal variations in the relative importance of parts of the network are studied as well. In [24] the evolution over 200 years of a North Milan road network is observed. Two main processes can explain the processes that occur. Densification of the road network around the main roads and emergence of new roads as a results of urbanisation. In conclusion even if the network was once optimally planned, it will probably become suboptimal as a result of changes in both the travel patterns and the network itself.

In order to analyse traffic one needs a model. Dynamic traffic assignment models such as the one described in [25] need a dynamic network load model and routing choices of agents model, which basically means that they need the OD matrix combined with a routing model such as in [26] based on stochastic conditions. Commuting patterns seem not to vary excessively as observed in [27]. It is shown that daily traffic is highly predictable and that there exist regular patterns that can be exploited. This stability of choices made by traffic participants together with network topology also leads to traffic concentration on mainly a few links of the network as shown in [1].

III. MEASURING THE DYNAMIC FACTOR OF NODES AND THE WHOLE NETWORK

In this section we introduce the dynamic factor of nodes. We define a node as dynamic if many vehicles (agents) pass through it and if the choices that agents make at this node vary abruptly. In order to measure the variation of agent choices we need to calculate the evolution of turning probabilities of agents in time. After that we simply weigh it by the throughput of agents. In this way we can measure how big and how fast are the variations at the nodes combined with how central their role in the traffic is. Let us introduce some notation that will be used throughout the paper first:

- N_{ij} - number of cars that moves from node i to node j for the whole day
- P_l - the path of the l -th agent
- f_{ij}^l - function that equals 1 if the sequence of nodes ij is in the path of agent l and 0 otherwise
- A - a set containing all the agents
- p_{ij}^t - probability that an agent that is at node i will continue on to node j during time period t
- S_i - set of nodes that are successors to node i
- N_{ij}^t - number of cars that pass sequentially through node i and j during time period t
- T - number of regions the day is split into
- L - length of a time period
- V_{ij} - variation of traffic on the road segment between nodes i and j
- V_i - variation of traffic at node i
- D_{ij} - dynamic factor on road segment between nodes i and j
- D_i - dynamic factor at node i
- C_i - capacity of a node w_i - average number of lanes associated with a node G_{ij}^t - congestion factor of road segment between nodes i and j for time period t
- \hat{D}_{ij} - normalised dynamic factor on road segment between nodes i and j
- \hat{D}_i - normalised dynamic factor at node i
- M - dynamic factor of a city

In order to calculate the dynamic factor of an intersection and a whole system we follow the procedure described below:

1) Calculate turning probabilities:

Let N_{ij} be the number of cars that pass through the i -th node and after that through the j -th node and let P_l be the path of the l -th agent. Then let the function f_{ij}^l :

$$f_{ij}(P_l) = \begin{cases} 1 & \text{if nodes } ij \text{ are in } P_l \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Then:

$$N_{ij} = \sum_{l=1}^{|A|} f_{ij}^l(P_l) \quad (2)$$

, where $|A|$ is the number of agents.

Let p_{ij}^t be the probability that an agent at node i continues to node j during time period t

Let S_i be the set of nodes that are successors of node i . Then we can define the turning probability as the ratio between the number of cars that pass through node i

and then proceed to node j and the total number of cars that pass through node i :

$$p_{ij}^t = \frac{N_{ij}^t}{\sum_{k \in S_i} N_{ik}^t} \quad (3)$$

2) Calculate the variation of turning probabilities at nodes:

The variation of the turning probabilities is calculated using a measure of slowness similar to [28]. The derivative of the probability evolving through time is examined. High values of the absolute value of this derivative mean high degree of variation of the turning probabilities and vice versa as we can see in equation 4. The term $\langle \rangle_t$ is used to depict averaging over t .

It is interesting to point out that we have chosen to use the derivative to determine the degree of variation rather than the more natural choice which would be the variance. The reason for this lies in the fact the our observations are sequential. We observe the change of turning probabilities in time and the sequence in which these changes occur matters for us. Therefore, a measure that takes into account this factor such as computing the derivative is preferred over the variance, which is intrinsically order invariant. Moreover, we are interested in the dynamics of the changes of behaviour at the nodes rather than their deviation, and naturally the changes in a time series are observed by examining their derivatives.

Since we are examining intersections, we need to look at all the successors of a node in order to evaluate the variation of the node itself. Therefore, we define the variation of a node as the average of the variations of the turning probabilities associated with it as shown in equation 5. We use the average instead of a simple summation in order to avoid intersection with static properties but many possible transitions to have high variation value.

$$V_{ij} = \langle \|\dot{p}_{ij}^t\| \rangle_t \quad (4)$$

$$V_i = \frac{\sum_{k \in S_i} V_{ik}}{\|S_i\|} \quad (5)$$

3) Weight the variation of every node with the number of agents that pass through it:

In order to differentiate between nodes that have a variation value that have high or low traffic throughput, we weigh the variation of every node by the number of agents utilising it. The dynamic factor of a node i is defined as in equation 7. It represents how fast is the activity at this node changing. More precisely, it represents how rapid and diverse are the changes in the choices that agents make at this node. Therefore, the nodes that experience rapid changing dynamics and are central in the sense of traffic demand will receive a high dynamic factor value.

More precisely, the change in traffic demand throughout one time period is weighed by the number of agents that pass through the node during this time. In this way, in case of a big change that does not affect many agents the dynamic factor is still small. Moreover, we are taking the logarithm of the flow since, we are mainly interested in the change of the turning probabilities. The term that includes the volume of cars is added in order to distinguish between busy intersections and ones that have very small throughput since the latter may not have such a big effect on the global traffic. In case the dynamic factor is calculated with the original flow, busy intersections that do not have that much variation in turning probabilities will get very high dynamic factors.

$$D_{ij} = \left\langle \|\dot{p}_{ij}^t\| \log \sum_{j \in S_i} N_{ij}^t \right\rangle_t \quad (6)$$

$$D_i = \frac{\sum_{k \in S_i} D_{ik}}{\|S_i\|} \quad (7)$$

- 4) Extension for Calculating the Dynamic Factor of a Network In order to extend this methodology to compute the dynamic factor of a whole network, our measure should be normalised in order to be universal for every different network. The term that actually needs normalisation is the number of vehicles that pass through the node. Some cities might experience more traffic than others, while the infrastructure can still take support it. In order to be able to compare one city to another a more global measure must be used. We propose a congestion factor that constitutes the flow over the node over its capacity as shown in equation 10.

$$w_i = \frac{\sum_{j \in S_i} w_{ij}}{\|S_i\|} \quad (8)$$

$$C_i = 2000Lw_i \quad (9)$$

$$G_{ij}^t = \frac{N_{ij}^t}{C_i} = \frac{N_{ij}^t \|S_i\|}{2000L \sum_{j \in S_i} w_{ij}} \quad (10)$$

In order to calculate this we also need to know the capacity of the node. The capacity of a link is defined as the number of lanes multiplied by a standard number of cars that can pass per lane per hour [29]. In order to get the capacity of the node we simply take the average of the capacities of the roads that are connected to it. Now after we have our normalised measure of flow, we can replace the flows in the dynamic factor formula with the normalised measure as shown in equation 12. Since the traffic flow is already normalised we do not need to take the logarithm anymore.

$$\hat{D}_{ij} = \left\langle \|\dot{p}_{ij}^t\| \sum_{j \in S_i} G_{ij}^t \right\rangle_t \quad (11)$$

$$\hat{D}_i = \frac{\sum_{k \in S_i} \hat{D}_{ik}}{\|S_i\|} \quad (12)$$

If the dynamic factor of every node is calculated then a distribution of the dynamic factors in the whole network can be accumulated. In order to compare the dynamic factors of the traffic conditions of two or more cities one will need to compare those distributions. We define the dynamic factor of a city M as the generalised mean with power factor $\alpha = 2$ of the distribution of \hat{D}_i as in equation 13. The generalised or power mean is used in order to put an emphasis on the extreme values in the distribution that make the network more dynamically changing.

$$M = \left(\frac{1}{N} \sum_{i=1}^N \hat{D}_i^\alpha \right)^{\frac{1}{\alpha}} \quad (13)$$

IV. MODEL AND CASE STUDY

The crucial type data that needs to be acquired in order to compute are the traffic flows time series along the edges of the network. From it the turning probabilities and, therefore all dynamic measures can be extracted. In order to apply the defined measures we should create a realistic scenario in order to evaluate them. We have chosen the city of Singapore with population 5.4 million people spread over 715 squared km of land area and around 1 million registered vehicles. It is an island city, which further simplifies the scenario since there is no significant flow of vehicles in or out of the city. There are 652 km of major arterial roads and 161 km of express ways in the city. The scenario for our experiment is as follows:

A. Agent Generation:

The data source used for agent generation is the Household Interview Travel Survey (HITS) of Singapore conducted in 2012. It contains information of a representative sample of people (about 0.7 % of the population) that among other demographic data also state their daily travel patterns. The information about all trips that are made on a daily basis consisting of origin point, destination point and starting time of the trip can be extracted for every surveyed person. We use those “sample” points from the population in order to construct an origin destination matrix describing the traffic demands in the city and their variation in time.

The OD matrix is used in order to generate a realistic number of agents with itineraries that consist of several trips throughout the day (depending on the agent) consisting of origin, destination and a start time. The sampling procedure basically consists of choosing one itinerary from the survey data at random and then adding noise to it in both space and time domains (sample random origins and destinations from a neighbourhood around the original ones and add mean 0 Gaussian noise to the starting time). The total number of agents that we generate is around 300,000 with starting times of trips varying throughout the day. Most of the agents have two trips in their itineraries, one in the morning (between 6 : 30 and 9 : 30) and one in the evening (between 5 : 30 and 7 : 30), however there is traffic in the city throughout the whole day.

Since it is not practical to visualise all OD pairs simultaneously, in our visualisation of the results of the agent generation process at Fig. 2 we are showing explicitly the intensities of OD pairs that have as origin the university area around the Nanyang Technical University (NTU) in the western part of the city. We can observe a concentration of trips within the university area, which represents students and faculty choosing to reside in proximity to their work place and intense movements towards the down town or central business district (CBD) area in the south central part.

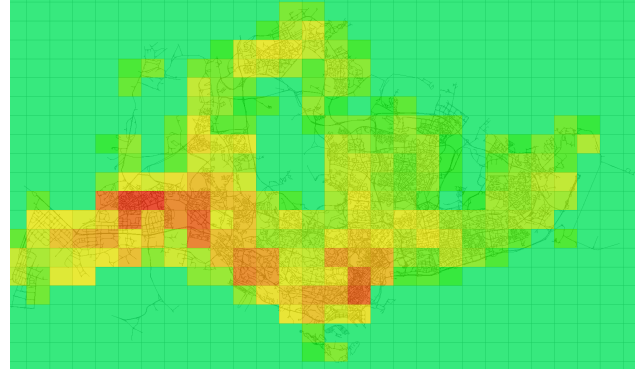


Fig. 2: Visualisation of the intensity of trips within Singapore with origin NTU (western part). The data is a result of the agent generation process described in section IV with data used from HITS 2012. Green colour represents low intensity, while red colour represents high intensity.

B. Route Calculation:

After all agents and their itineraries are generated, the origins and destinations of their trips are used to calculate the actual routes that will be taken. In order to represent this process as realistically as possible the routing of the generated agents is stochastic. Some people prefer the shortest path, some the fastest and some have a preference comfort rather than speed or time. We, therefore, have 3 different ways to calculate our routes. We are able to realize the distinct routing types by calculating the weights on our routing graph in a different way. After that we use a shortest path algorithm that minimizes the sum of the weights for a path between origin and destination. The three types of weights are:

- 1) $w_d = \text{road length}$ - minimising distance
- 2) $w_t = \frac{\text{road length}}{\text{road speed}}$ - minimising time
- 3) $w_c = \frac{\text{road length}}{\text{road speed} \times \text{number of lanes}}$ - maximising comfort

and the probabilities that an agent has a certain preference have been set to $\frac{1}{3}$ for each type of weights, which is in agreement with literature about route choices as [30].

After the generation of every agent one of the three preferences is chosen at random and the corresponding route is calculated. After the paths are computed, the sequence of links that every agent passes through is then used in order to calculate the turning probabilities. The day is split into 48 pieces consisting of 30 minute intervals. In order to calculate the dynamic factor of every node for the whole day, the starting time of the trip is used as a time-stamp of the whole route and in this way the passages through links in time are organized. The measure is calculated as described in section III.

C. Dynamic Factor Calculation

In order to visualise our results in a better way, we have calculated the dynamic factors only of the nodes that have a significant throughput, which we set to be more than 10000 cars per day. Even though, we account for the flow of vehicles in the definition of the dynamic factor it will still give a better picture if in our results we are only concerned with central intersections. After calculating the dynamic factor of every node that satisfies our constraints a distribution of the dynamic factors throughout the network is acquired as shown in Fig. 3

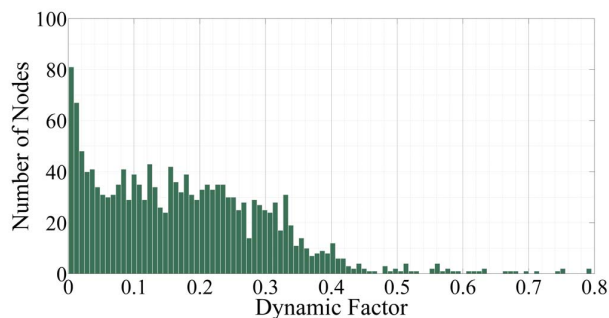


Fig. 3: Histogram depicting the distribution of Dynamical Factor values in the Singapore road network. Only intersections with daily throughput higher than 10000 cars are taken into consideration.

It can be observed that the distribution can be split into three main parts. The first part consists of many nodes with a dynamic factor close to 0. Those are most probably on and off ramps to the highways and major arterial roads. Naturally there the turning probabilities are more or less stable, however, the throughput is still high and that is the reason they appear on the graph. The second part of the distribution is the uniform portion between 0.05 and 0.35. Here we probably observe standard degrees of variation at the nodes with varying flows of vehicles. The third, and most interesting part of the distribution is the one that contains very few intersections with relatively high dynamic factors. It seems like the distribution has a fat tail and the nodes contained in the far right part exhibit very dynamically changing turning probabilities and high traffic of vehicles. These are the intersections that present the biggest challenges for control and road infrastructure planning. A rule of thumb for identifying the critical intersections would be to examine all nodes have dynamic factors high enough to be

in the third segment of the distribution. This threshold value can be determined by visual inspection and may vary among different cities. On Fig. 4 we see the evolution in time of the turning probabilities of the most “dynamic” node in the network. We can observe that all three options that the drivers have are varying abruptly in time and that every option is being the most preferred one during at least one period of the day.

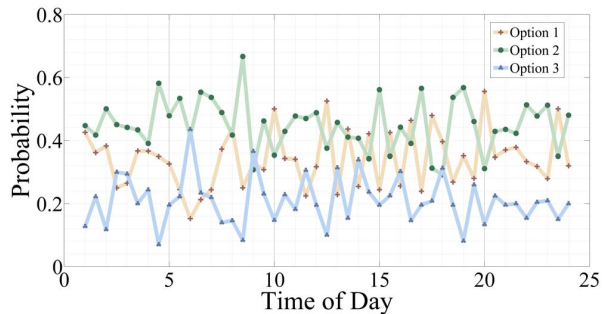


Fig. 4: Turning probabilities of the most dynamic node according to our model in the city of Singapore. The distinct time series represent the probability that a car would choose the corresponding outgoing road from the intersection throughout the day.

The highly non-uniform distribution can also be observed in the spatial distribution of the dynamic factor as shown in Fig.5. There are several very dynamic locations that are either intersections between major roads or are connecting residential and business areas. The latter case presents high dynamic factors due to the qualitatively different demands in the morning and evening. The first type presents changes due to a constant dynamic nature of events at those intersections. We can also observe a cluster of points with high dynamic factor at the central business district (south central part), which can be due to the high concentration of business offices and constant movement of commuters within this area.

V. CONCLUSION

In this paper we have pointed out the possible existence of intersections in large cities that may experience unusually dynamical behaviour throughout the day which is manifesting itself in fast changing of the preferred turns by the traffic participants. If this is combined with high volume of vehicles passing through, such type of locations can be solely responsible for traffic jams and worsened performance of any implemented control strategy, which makes the identification of such “hot spots” an important task.

The measure of the dynamic factor is defined in order to quantify the dynamics of an intersection and to provide a full picture of the network itself. We have presented a topological analysis method that combines the spatial and temporal properties of traffic and is able to identify intersections that have uniquely abrupt and fast changing dynamics combined high traffic flow and, therefore, present a challenge for control.



Fig. 5: Spatial distribution of dynamic factor of intersections in Singapore according to simulated agent routes. Big red dots mean high dynamic factor and small green dots mean low dynamic factor. Only intersections with throughput higher than 10000 cars per day are considered.

Furthermore, we have defined a dynamic factor measure extension in order to universally quantify the dynamics of the whole network in order to compare it to other city's road infrastructures.

We have carried out a case study to test our methods with real data from the city of Singapore. Using an extensive survey database we were able to generate a realistic traffic demand within the city and model the routing choices of the commuters throughout the day. We have applied our methods in order to identify and locate the central intersections that demonstrate extensively dynamical behaviour. We have observed the distribution of the dynamic factor measure throughout the network. It was shown that it has a fat tail on its positive side, which means that there are few intersections that demonstrate very dynamic behaviour and have a high throughput, which coincides with our initial hypothesis.

As a further research steps it might be interesting to compare the dynamic profile of the intersections in Singapore to other cities. This is, however, subject to data availability. Moreover, such an experiment can be used to verify the results of this study by ensuring that intersections with high dynamic factors exist in other cities as well. By comparing distributions of the dynamic factors we can also check for qualitative differences between cities and traffic organisation. Traffic in Singapore is considered to be fairly well organized compared to mega polices that have organisational and financial hardships. We

expect that the degree of inequality of the distribution of dynamical factors will be even higher for such traffic systems.

It would also be interesting to check if the characteristic turning probabilities at intersections are in agreement with the number of lanes on the respective roads. Varying turning probabilities inevitably bring imbalance of traffic on the network as some roads become congested while others stay empty. It is possible that as the traffic demand changes some roads become obsolete or their high capacity is no longer required, while other roads must accommodate higher throughput. Following this argument it might be interesting to use the turning probabilities at the nodes in a network in order to point out to such locations where the topology of the network no longer meets the needs of the traffic demand.

ACKNOWLEDGEMENT

This work was financially supported by the Singapore National Research Foundation under its Campus for Research Excellence And Technological Enterprise (CREATE) program.

REFERENCES

- [1] S. Lämmer, B. Gehlsen, and D. Helbing, "Scaling laws in the spatial structure of urban road networks," *Physica A: Statistical Mechanics and its Applications*, vol. 363, no. 1, pp. 89 – 95, 2006, information and Material Flows in Complex Networks Information and Material Flows in Complex Networks. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0378437106000938>

- [2] E. Beukes, M. Vanderschuren, and M. Zuidgeest, "Context sensitive multimodal road planning: a case study in cape town, south africa," *Journal of Transport Geography*, vol. 19, no. 3, pp. 452 – 460, 2011, special Issue : Geographic Information Systems for Transportation. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0966692310001341>
- [3] F.-Y. Wang, "Parallel control and management for intelligent transportation systems: Concepts, architectures, and applications," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 11, no. 3, pp. 630–638, Sept 2010.
- [4] C.-L. Fok, M. Hanna, S. Gee, T.-C. Au, P. Stone, C. Julien, and S. Vishwanath, "A platform for evaluating autonomous intersection management policies," in *Cyber-Physical Systems (ICCPs), 2012 IEEE/ACM Third International Conference on*, April 2012, pp. 87–96.
- [5] K. M. Yousef, M. N. Al-Karaki, and A. M. Shatnawi, "Intelligent traffic light flow control system using wireless sensors networks." *J. Inf. Sci. Eng.*, vol. 26, no. 3, pp. 753–768, 2010.
- [6] M. Dehmer and A. Mowshowitz, "A history of graph entropy measures," *Information Sciences*, vol. 181, no. 1, pp. 57 – 78, 2011. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0020025510004147>
- [7] R. L. Gordon, "A technique for control of traffic at critical intersections," *Transportation Science*, vol. 3, no. 4, pp. 279–288, 1969. [Online]. Available: <http://dx.doi.org/10.1287/trsc.3.4.279>
- [8] M. Aymerich and A. Novo, "Madrid critical intersections antiblocking strategies," in *Road Traffic Monitoring, 1992 (IEE Conf. Pub. 355)*, 1992, pp. 70–.
- [9] M. Dongfang, S. Xianmin, T. Pengfei, and W. Dianhai, "Critical traffic volume warrant of signal installing at equal weight intersections," in *Intelligent Computation Technology and Automation (ICICTA), 2011 International Conference on*, vol. 1, March 2011, pp. 388–391.
- [10] G. Stephanopoulos and P. Michalopoulos, "Real time control of critical intersections based on queue dynamics," in *Decision and Control including the 17th Symposium on Adaptive Processes, 1978 IEEE Conference on*, Jan 1978, pp. 1018–1024.
- [11] S.-X. Yuan, Y.-S. An, X.-M. Zhao, and H.-W. Fan, "Modeling and simulation of dynamic traffic flows at non-signalized t-intersections," in *Power Electronics and Intelligent Transportation System (PEITS), 2009 2nd International Conference on*, vol. 2, Dec 2009, pp. 1–5.
- [12] L. Qian and X. Chen, "Peak volume characteristics of urban road intersections: Case in shanghai," in *Computer and Network Technology (ICCNT), 2010 Second International Conference on*, April 2010, pp. 397–401.
- [13] Y. Hu and J. Hellendoorn, "Daily traffic volume modeling based on travel behaviors," in *Networking, Sensing and Control (ICNSC), 2013 10th IEEE International Conference on*. IEEE, 2013, pp. 639–644.
- [14] W. A. M. Weijermars, *Analysis of urban traffic patterns using clustering*. University of Twente, 2007.
- [15] D. M. Scott, D. C. Novak, L. Aultman-Hall, and F. Guo, "Network robustness index: A new method for identifying critical links and evaluating the performance of transportation networks." *Journal of Transport Geography*, vol. 14, no. 3, pp. 215 – 227, 2006. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0966692305000694>
- [16] H. Corley and D. Y. Sha, "Most vital links and nodes in weighted networks," *Operations Research Letters*, vol. 1, no. 4, pp. 157 – 160, 1982. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/0167637782900207>
- [17] M. Schreckenberg and R. Selten, *Human behaviour and traffic networks*. Springer, 2004.
- [18] S. Porta, V. Latora, F. Wang, S. Rueda, E. Strano, S. Scellato, A. Cardillo, E. Belli, F. Cardenas, B. Cormenzana *et al.*, "Street centrality and the location of economic activities in barcelona," *Urban Studies*, vol. 49, no. 7, pp. 1471–1488, 2012.
- [19] E. Jenelius, "Network structure and travel patterns: explaining the geographical disparities of road network vulnerability," *Journal of Transport Geography*, vol. 17, no. 3, pp. 234 – 244, 2009. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0966692308000550>
- [20] F. Xie and D. Levinson, "Measuring the structure of road networks," *Geographical Analysis*, vol. 39, no. 3, pp. 336–356, 2007. [Online]. Available: <http://dx.doi.org/10.1111/j.1538-4632.2007.00707.x>
- [21] J. Budiarto, S. Sulisty, I. Mustika, and A. Infantono, "Road density prediction: Updated methods of turning probabilities and highway capacities manual for achieving the best route," in *Electrical Engineering and Computer Science (ICEECS), 2014 International Conference on*, Nov 2014, pp. 168–173.
- [22] A. Erath, M. Löchl, and K. W. Axhausen, "Graph-theoretical analysis of the swiss road and railway networks over time," *Networks and Spatial Economics*, vol. 9, no. 3, pp. 379–400, 2009.
- [23] F. Xie and D. Levinson, "Topological evolution of surface transportation networks," *Computers, Environment and Urban Systems*, vol. 33, no. 3, pp. 211 – 223, 2009. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0198971508000653>
- [24] E. Strano, V. Nicosia, V. Latora, S. Porta, and M. Barthélemy, "Elementary processes governing the evolution of road networks," *Scientific reports*, vol. 2, 2012.
- [25] M. Sanchez-Rico, R. Garcia-Rodenas, and J. Espinosa-Aranda, "A monte carlo approach to simulate the stochastic demand in a continuous dynamic traffic network loading problem," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 15, no. 3, pp. 1362–1373, June 2014.
- [26] T. xing and X. Zhou, "Reformulation and solution algorithms for absolute and percentile robust shortest path problems," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 14, no. 2, pp. 943–954, June 2013.
- [27] Y. Li, D. Jin, P. Hui, Z. Wang, and S. Chen, "Limits of predictability for large-scale urban vehicular mobility," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 15, no. 6, pp. 2671–2682, Dec 2014.
- [28] L. Wiskott and T. J. Sejnowski, "Slow feature analysis: Unsupervised learning of invariances," *Neural computation*, vol. 14, no. 4, pp. 715–770, 2002.
- [29] R. Roess and W. McShane, "Changing concepts of level of service in the 1985 highway capacity manual: some examples," *ITE Journal*, vol. 57, no. 5, 1987.
- [30] S. Bekhor, M. E. Ben-Akiva, and M. S. Ramming, "Evaluation of choice set generation algorithms for route choice models," *Annals of Operations Research*, vol. 144, no. 1, pp. 235–247, 2006.