Understanding sudden traffic jams: From emergence to impact

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ABSTRACT

Road traffic jams are a major problem in most cities of the world, resulting in massive delays, increased fuelwastage, and monetary and productivity losses. Unlike conventional computer networks, which experiencecongestion due to excessive traffic, road transportation networks can experience traffic jams over prolongedperiods due to traffic bursts over short time scales that push the traffic density beyond a threshold jamdensity. We observe that the emergence of such jams can happen over a very short duration, hence we term them assuddentrafficjams. We provide a formalism for understanding the phenomena of sudden traffic jams and showevidence of its existence using loop detector data from New York City. Further, we show the signature of suddenjams when observed at hourly resolution. We also provide a method to compute the traffic curve in a situationwhere we do not have access to fine-grained flow and density information. With this method, using only hourlyspeed data from Uber, we compute traffic curves for the road segments in Nairobi, S o Paulo, and New YorkCity, which is, by our knowledge, the first attempt to do so for signalized road networks. Running our analysison the Uber movement speed data for the three cities, we show numerous instances of jams that last severalhours, and sometimes as long as 2 3 days. Empirically, we find that Nairobi experiences 3x the mean jamtime per road segment as compared to S o Paulo and New York City. Based on key development metrics, wefind that the ratio of traffic load per road segment for S o Paulo, New York City, and Nairobi is approximately

1:2:3. We propose that chaotic driving patterns and traffic mismanagement in the developing world citieslead to tighter traffic curves, more intense jams and overall lower road capacity utilization, which explainsthe observed data. We posit that the problem of traffic congestion in developing countries cannot be solvedentirely by building new infrastructure, but also requires smart management of existing road infrastructure.

1.Introduction

Poor road traffic management can trigger extended periods of trafficcongestion, as is witnessed in most parts of the world. As per TexasTransportation Institute s 2009 Mobility report (Texas Transportation Institute), congestion in the US has increased substantially over the last25 years with massive amounts of losses pertaining to time, fuel, andmoney. In the top 10 cities with the worst levels of congestion in theworld, the average number of hours wasted per commuter per yearis over 150 h (Friedman, 2020). When the number of hours wastedexceeds about 35 h per year, it is observed to affect the economy nega tively (Badger, 2013). This kind of prolonged traffic congestion persistsin many large urban cities (TomTom International B.V.). Especially indeveloping regions, with poorly managed road networks and freeways,

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this remains an important barrier to economic development in these regions. Reducing traffic jams improves the quality of life also in the form of improved air quality. A report on the air quality study in Delhi attributes nearly 20% of PM concentration in the air to traffic (Sharma and Dikshit, 2016).

Traffic congestion can be both good and bad (Badger, 2013). A certain level of congestion, especially in dense urban regions, may indicate economic prosperity and thriving economic development, as in many major cities. However, commuters wasting away their time in jams that last for hours, such as on freeways, is an example of bad congestion. We explore the issue of such bad congestion occur rences that happen mostly due to a sudden burst in traffic density. Contrary to the conventional belief that traffic congestion is triggered

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Fig.1.Traffic on the Williamsburg bridge in New York City.

due to excessive traffic, traffic jams for elongated time periods, suchas several hours, can actually be triggered by small traffic bursts oversmall timescales (Jain et al., 2012; Kerner and Rehborn, 1996). Theunderlying cause of the traffic jam is not due to the lack of roadcapacity, but due to a spiraling effect triggered by a small burst thatpushes the road traffic network to a low-capacity equilibrium point.This equilibrium point is highly stable and the only way to recover fromthis is to dramatically reduce the input flow into the traffic network anddrain the congested network. This phenomenon occurs because trafficlinks exhibit a traffic curve behavior where the capacity of a link isvariable dependent on the traffic density on any link; any input flowbeyond the optimal operational rate over a short time that triggers thedensity beyond a critical threshold automatically triggers a spiralingeffect resulting in a traffic jam. We refer to any jam caused this way as a suddentrafficjam. It should be noted that this spiraling phenomenonis different from the disturbance propagation phenomenon that resultsin phantom jams (Treiterer and Taylor, 1966; Treiterer and Myers,1974) as this is a feature of the traffic curve rather than microscopicperturbations emerging spontaneously.

Traffic collapse results when the traffic density on a link exceedsa certain threshold. The operational free-flow exit rate of the link,which determines how quickly the link is drained, varies with the trafficdensity (May, 1990). Each traffic link reaches an optimal capacityat a corresponding optimal operating density, beyond which the exitrate rapidly drops. In New York City, consider the exit point of theWilliamsburg bridge on the Manhattan side (Fig. 1). A traffic lightimmediately follows the bridge, and numerous vehicles are regularlystuck there for several minutes, especially during the morning andevening rush hours. The graph shown in Fig. 1(b) is a plot of the trafficcongestion at the exit point of the Williamsburg bridge. The ..-axis is the measure of the vehicle density, or the traffic density, on the road. The ..-axis represents the time in seconds after 14:50:40 when the trafficwas observed. By manual inspection of the camera feed, we are ableto determine the minand maxdensities as well. The max density isa density value above which there is complete congestion, whereasthe minis a value below which there is no congestion at all. In thisparticular example, the min and max values were determined to be68 and 39. The congestion can be mitigated if the input rate of thevehicles into the bridge is controlled before it reaches the tipping pointfor congestion collapse.

Our contributions in this paper are the following:

We introduce the concept of sudden traffic jams, provide a formaldefinition, and illustrate the signature of such jams on speed dataaveraged at hourly resolutions using loop detector data from New York City (New York City Department of Transport). Based on thishourly signature, we propose a heuristic definition of jams (calledslowdown jams) for hourly resolution speed data. Using hourlyresolution Uber Movements speed data (Uber Technologies), wecompute the occurrences and statistics of slowdown jams in threecities Nairobi, S o Paolo, and New York City.

We also provide a method to compute the traffic curve in asituation where we do not have access to fine-grained flow anddensity information. Using this method, we compute traffic curvesfor a large number of segments in each of the three cities. Toour knowledge, the concept of traffic curves for signalized net work conditions was a hypothetical assumption that has not beenvalidated and this is the first attempt to do so.

Using the derived traffic curves and a simple definition of a trafficjam, we have been able to show how a traffic jam can quicklyemerge within a short time period and we also show that oncea jam is hit, it often takes a long time to recover from a jam.We have validated these points in our analyses using multipledatasets.

The larger implication of our findings is very significant for de velopment engineering. Developing countries invest large amounts toupgrade road networks in urban cities to address traffic congestion. Wepicked two cities in developing countries (Kenya and Brazil) and onedeveloped and highly industrialized city (New York City). We showwith the findings of our analysis that the ratio of mean time spentin jam per road segment for S o Paulo, New York, and Nairobi isapproximately 1:1:3. Using key development metrics, we also showthat the corresponding ratio of traffic load per road segment is ap proximately 1:2:3. Thus, we infer that developing world cities likeNairobi and S o Paulo have lower road capacity utilization (almost0.5x) compared to a developed world city like New York City. Thispaper shows that addressing the traffic congestion problem for urbancenters in developing countries is not just about building more roadsbut actually more about careful traffic management.

We build specifically on one piece of prior work (Jain et al., 2012)which provided a hypothesis for what triggers traffic congestion indeveloping countries using the concept of traffic curves. The concept oftraffic curves, which are very popular in highway traffic networks, hadnever been used in the context of signalized networks to understandtraffic flow. In 2012, there was very limited traffic flow data, especiallyin the context of developing regions that could really help with thesudden traffic congestion phenomenon. It was hypothesized in thepaper by Jain et al. that the sudden traffic congestion phenomenonwas a particular problem at several urban choke points in developing countries, especially with the lack of good traffic management andchaotic driving with high densities of car packing. Once we hit a trafficjam triggered by a sudden burst, it is very hard to recover from it forseveral hours unless inbound traffic is carefully managed.

The rest of the paper is structured as follows. First, we presentrelevant literature on traffic jams. Then we provide definitions andformalism of traffic curve and sudden traffic jams, followed by il lustrations of sudden jams in the real world. Then we provide thecharacterization of observed sudden jams for three different cities New York City, Nairobi and S o Paulo. Finally, we conclude the paperwith our takeaways.

1.1.Priorart

Modeling of traffic flow has been a subject of study for severaldecades, since the 1950s (Orosz et al., 2010). There are two primary ways to model traffic flow macroscopic (continuum) models andmicroscopic (car-following) models. In the former, a relationship be tween traffic density and speed is established in the form of a partialdifferential equation. This allows us to define jams precisely as stop and-go events. However, this requires high-quality data on the trafficdensity, whereas in practice, most available data from existing instru mentation in cities or probe vehicles or other mobile sources are eithertravel time data or travel speed data. The latter is even more difficultin practice owing to the large number of parameters required for themodel. Zhao et al. (2016) define the concept of resilience in trafficflows to understand how quickly we can recover from jams in the realworld. Stathopoulos and Karlaftis (2002) model the amount of timetaken for jams to drain as a function of the jam duration. They showthat the log-logistic functional form, similar to the form of the trafficcurve discussed in Section 3.1, is the best approximation. They alsofind that if a jam lasts beyond a threshold value of around 20 min, it ismost likely caused by external factors and will last a long time. Knorr et al. (2012) propose a strategy to prevent the occurrence of traffic jamsby enabling driver-to-driver communications, thus informing drivers ofimpending congestion ahead. The drivers then slow down and maintaina greater inter-car distance. Through simulations, they report thatpenetration rates of 10% or less in a city can have a significant influenceon traffic flow.

Short-term traffic prediction and forecasting is a related topic thathas a long history in the academic community. The challenge is toidentify traffic flow patterns at some point in the future; commonlybetween one and five minutes, but generally between one minuteand an hour. Much of the foundational work in short-term traffic comes from models based on time series analysis; Kalman filteringand the ARIMA-family of models, for example. Recent work has takena machine learning approach, modeling the regression using supportvectors, neural networks (Iyer et al., 2020), graphical models (Hu et al., 2016), and pattern matching. For summaries, see Vlahogianni et al. (2014) and Oh et al. (2015).

When classifying traffic state, researchers are essentially trying tobin a snapshot of road condition into a particular state, sometimesknown as a levelofservice. Levels of service are sometimes estab lished using well-known standards, such as the Transportation ResearchBoard s Highway Capacity Manual, but are sometimes more subjective,using an array of human judgment. Porikli and Li (2004) and Lozano et al. (2009), for example, analyze images from traffic cameras todetermine roadway conditions; Sen et al. (2013) use video feeds to accurately estimate traffic speed and density; Roy et al. (2011) usestrategically placed Wi-Fi transmitters to monitor traffic state. Ratherthan determine traffic state specifically, Yang et al. (2014) use loopdetector data to detect changes in flow. What is common across suchwork, however, is the need to obtain volume data from the underlyingdata set. That is, an estimate of the density of traffic at a given time.In this work, such information is not provided, nor can it be inferred; thus, existing techniques from the density community are not directly applicable.

One alternative is to use speed information to determine the trafficstate. Doing so requires a different process for establishing levels ofservice, as what speed means to traffic jams is relative to a notionof free flow at a given point. In the absence of this information, re searchers either have to establish a meaning of speed-versus-jam usinghuman judgment (Pattara-Atikom et al., 2006), or use novel techniques to create their own (Yoon et al., 2007). Irrespective of the nature of thedata whether it contains speed, volume, or a combination of both existing work has largely focused on highway data. A notable exceptionbeing Yoon et al. (2007), who consider a suburban stretch containing traffic signals.

2.Materials

2.1.NewYorkCitydepartmentoftransportationdata

This data comes from the City of New York Department of Trans portation (nycdot). The department provides a website (New York City Department of Transport) that publishes traffic information forvarious traffic segments throughout the five boroughs of New York City;there are currently 153 such segments. Each segment has a name, aunique identifier, and location data. The name is a string describingthe segment as most resident travelers would, FDR, north 25th at 63rdstreet, for example. The location data consists of a polyline, suitablefor understanding the geography of the segment and placing it on a map.

Along with basic information, measurements come with a times-tamp and two types of speed data: the average vehicular speed over thesegment, and the average time required to traverse the segment. In the ory, each signal is continuous its timestamp representing a snapshot.In practice, and due to limitations in polling, the information is updatedeach minute. Thus, although the timestamp is at the granularity ofseconds, it can be resampled to the granularity of minutes without lossof generality.

However, the reporting reliability at each segment varies, so notall segments have reports for each minute. Further, periodic systemdowntime, on both the reporting and collection end, prevented com plete continuous polling. For a section of the data collected betweenNovember 2014 through April 2016, on average, a segment consists ofapproximately 513,000 measurements instead of the expected 740,000measurements. Inter-polling statistics the average amount of timebetween traffic measurements is one way of describing a segments reliability. For the above-mentioned section of the data, the averageinter-polling time across all segments was approximately 7.85 minutes,however that number is dominated by a few very unreliable segmentsas the standard deviation is almost 63 minutes. In the best case, thereis a measurement every 66.88 seconds; in the worst, every 12.72 h.Fig. 2(b) presents a distribution of average reporting times across the signals.

2.2.UbermovementsspeeddataforNairobi,NewYorkCityandS oPaulo

We analyzed the Uber Movements data for Nairobi city in Kenya,New York city in the United States of America, and S o Paulo in Brazilto study sudden traffic jams (Uber Technologies). The data has hourlyaverage speeds in all road segments in the city. Every segment or way inthe dataset is defined as the stretch of road between two junctions. Eachroad segment has multiple nodes which are used to characterize thestops along the way, and the dataset consists of average speed valuesevery hour for every pair of source and destination nodes. To calculatethe average speed in a segment, all the individual speeds across allconsecutive pairs of source destination nodes in the segment wereaveraged. Each segment corresponds to a wayin OpenStreetMap (Open-StreetMap contributors, 2017), denoted by a ......\_...., and therefore we are able to look up these segments on a map.

Fig.2.Available segments in the loop detector data feed from NYC DoT from November 2014 to April 2016. The left plot shows the segments on the map, color-coded by the

reporting frequency, and the right side shows the distribution of reporting frequencies.

Fig.3.Cumulative distribution of hourly traffic speeds across all the segments in thecity of Nairobi.

We analyzed the dataset from January 2018 to March 2020. Thecities of Nairobi, New York, and S o Paulo have respectively 4949;35,602, and 89,121 segments respectively. Fig. 3 shows the cumulative distribution of mean segment speeds across all 4949 segments for thecity of Nairobi. From the data of Nairobi city, we notice that only 12%of the average speed exceeds the speed limit of 50 km/h (Hodge) and the average length of such a road segment is about 80 m long (Nesbitt and Dara-Abrams, 2017). We see similar behavior of speed distributionsfor NYC and S o Paulo. After sampling the mean speed time series ofeach segment using a Poisson distribution with .. =8 (for removingtemporal correlations), we put an assertion on the segments to haveat least 20 sampled points for generating reliable speed distributioncurves. After applying the above condition, we are left with 3063;25,371, and 53,658 segments for Nairobi, New York City, and S o Paulorespectively. In our downstream analysis, we take these segments andcompute traffic jams based on an hourly-resolution definition.

While one would like to validate the Uber Movements data usingother well-known sources of traffic data like Google Maps, etc, this exercise presents several hurdles in practice. We investigated the pos sibility of ground truthing the Uber movements dataset using googlemaps. The most notable obstacle in this attempt is that Google mapsdon t provide access to historical data. The Uber movement data for allcities ranges from 2018 2020, and comparing it with the google mapsdata at the time of writing this article requires assuming that the trafficpatterns have remained constant over the last 2 3 years. We considerthis assumption questionable since 2 3 years is sufficient time for theroad network and corresponding traffic conditions to change, especiallyin the context of developing countries. Another challenge is that Googledistance matrix API (google maps API) only gives travel-time estimatesbetween origin and destination points and does not give average speedper road segment. The Uber movement data also provides aggregatedand bracketed travel time estimates, but the travel time data has notbeen used much in our analysis. While one could validate the Ubertravel time data using google maps after taking the earlier assumption,one would have to further assume that the correctness of Uber travel time data implies the correctness of Uber speed data. Similar challengesemerge when other sources of data are considered for validation.

In fact, there has been a prior study validating Uber travel timedata against Google maps travel time predictions (Wu, 2018), thatmakes the constant traffic pattern assumption, albeit over a smallertime duration of 6 months for the city of Sydney, Australia. Wu (2018)notes that travel time from Google and from Uber is generally similarbut the observations from the Uber data are systematically lower thanGoogle s predictions. Differences in the data collection method (actualtrip time for Uber vs prediction for Google), as well as the correspond ing subtle intents and objectives (like faster trips for Uber vs reliableestimation for Google), have been attributed as possible causes of thisbehavior. Wu (2018) indicates that the Uber travel time data is likelyto be correct and potentially valid. Thus, by extension, we assume thecorrectness of the Uber speed data in all our downstream analyses.

3.Theoryandempiricalapproximations

3.1.Trafficcurveandtrafficcollapse

A transportation network is a collection of segmentsor links, wherea segment/link consists of a set of geographic coordinates representing

Fig.4.Traffic curves showing the instantaneous exit rate (left) and the maximum exit rate (right) as functions of the buffer size.

Fig.5.Merging of two freeways.

a polyline and a collection of observations. Observations are a familyof average speeds along and/or travel time across the polyline at aninstance in time: {(..,..)..}...N, where .. and .. are speed and travel time,respectively. For convenience and consistency with data, travel timeis dropped from the formalization, allowing the speed at time .. for a given segment .. to be denoted as simply ..... Every finite stretch of road, a link, can be associated with a trafficdensity, or the fraction of the link capacity that is occupied by vehicles, at a given time. Thismay equivalently be expressed by the buffersizeorbuffercapacity(.... ),which is the number of vehicles in the link. The exitrateor exitcapacity (.... ) of a link is defined as the number of vehicles exiting the linkper unit time. The traffic curve captures the variation between thesetwo parameters (Jain et al., 2012). At high traffic densities (indicatingtraffic jams), links have very low operational exit capacities and at lowdensities, the exit rate varies linearly with the density (Fig. 4). We define the optimal operating points of a traffic curve based on optimalexitrate.. \* where the exit rate is the highest and the corresponding .. \* ,

.. ..

the optimalbuffersizeat .. \*. Based on the traffic curve, one can define

..

the maximum exit rate of a link as a function of the current buffer capacity as shown in Fig. 4. The maximum exit rate is the maximum number of vehicles that can exit the buffer per-unit time, .... (.... (..)),which is also equal to the maximum sustainable flow rate at equilibriumfor a given buffer capacity.

Now, consider the case where the input rate is larger than theoptimal exit rate for a short time period, causing the link buffer togrow. Once the buffer size increases beyond the optimal value .. \* , the

..

exit rate begins to decrease, leading to a more rapid increase of thebuffer size, which further perpetuates the cycle, until a point is reachedwhen the buffer is full and the exit rate is at its lowest possible value.This is called a trafficcollapse. A very common real-world exampleis two freeways merging into a single freeway. A simple example isillustrated in Fig. 5, where vehicles in .. are merging with the stream in the setup: (a) ........ representing, a small segment of .. (coveringa short distance of up to 0.5 miles) before the merge point; (b) asmall segment .. before the merge point; (c) ........, representing a small segment of .. after the merge point. Each of the links can be associatedwith their corresponding traffic curves. Since we are dealing with adiscrete version approximation using traffic curves, we should choosereasonable lengths to have meaningful buffer values for the links. Theabove traffic merging can be viewed using a simple 3-link topologywhere ........ and .. merge into ........, and each segment has an associatedtraffic curve. We primarily concentrate on two specific parameters of ........: .... \*(........) and .... \*(........). If the sum total of the exit rates of ........and .. is always less than the optimal exit rate ..\*(........), then the

..

merging never faces a congestion problem. If, however, the sum of theinput rates of .. and ........ is larger than .. \*(........), then the buffer size

..of ........ grows. If the buffer of ........ grows beyond .. \*(........), then the

..exit rate of ........ begins to drop thereby, triggering the spiraling effect.

3.2.Identifyingsuddenjams

The phenomenon of traffic collapse as defined in the previoussection leads to a trafficjam, which is a prolonged state of very slowmovement of vehicles on the road. A road segment is said to be in astate of completejamwhen the density is maximum and the averagespeed of vehicles in the segment is 0 i.e. the vehicles have come to astandstill. Above a certain threshold of density, or equivalently, belowa certain threshold of the average speed of the flow of vehicles in thesegment, the segment can be said to be approachinga jam. The choice ofeither threshold is based on the range of possible speeds in the segment.We define suddenjamqualitatively as the state when we approach a jamquickly. That is, if the traffic collapse happens over a very short timeperiod (typically within a matter of minutes), then we call it a suddenjam. This can happen due to a rapid build-up in the buffer size, in turnresulting in a rapid drop in vehicle speeds in the segment. Sudden jamsare very common in congested cities all over the world (Jain et al., 2012).

Formally, a sudden jam may be defined as follows. Consider a pointin time .. in segment .. and .... be the corresponding time-series array of observation times. Let ...... be the index of time .. in ..... Consider two positive integers, .. and .. where .. < ... The predictionwindow is the interval (..,....(...... + ..)), and the targetwindow is [....(...... + ..),....(...... + ..)]. Further, let the observationwindow be an interval prior to .. that is the same size as the target window based on the number of observations: [....(...... -(.. - ..)),..].A suddenjamat time .. is a condition in which ac celeration between the target and observation windows is less-than, orequal to, some threshold ... Eq. (1) shows the mathematical definition of the sudden jam function.

(...+..

..=..+..

.... -

... ..=..-(..-..) ....

)

= ..

(1)

of vehicles on ... This simple example can be viewed in two ways: twolanes in the same freeway merging into a single lane or two separatefreeways merging or a single lane merging into a freeway. To visualize

this problem from the perspective of traffic curves, consider three links

....(..,..,..)=

.....

if 1

1

(....(..)-..) (..-..)

otherwise.

0

Fig.6.Examples of most segments (90%) where there were two clear break points in the CDF of observed speeds. We named these breakpoints ..1 and ..2 . The ..1 speed would beapproximately the point at which the traffic crosses the threshold density for a jam. These breakpoints were obtained by fitting a piecewise linear model to the CDF function.

Fig.7.Examples of some segments (10%) where the speed CDFs were different. There were no two clear breakpoints, hence not a well-defined threshold density to define a jam.Note that this is notan artifact of the amount of available data in these segments some of these segments had even more data available than those in the first set.

Essentially, there is a sudden jam if the average speed of the obser vation window differs from the average speed of the target window,hence the division by the window size .. - ... The additional factor in the denominator, ....(..)- .., is the temporal size of the target window,converting the derivation to one of acceleration, and allowing .. to be expressed as gravitational units. This not only allows the metric to beconsistent with the literature on sudden braking events (Harbluk et al., 2007; Simons-Morton et al., 2009), but removes biases toward segmentswith faster free-flows. By normalizing with respect to deceleration,the impact that the slow down has on the passenger remains relativelyconstant. We apply this definition in our New York dataset, where wehave speed data from very selected road segments, especially freeways,bridges, and tunnels, every minute, collected using loop detector instru mentation, from the local transportation department (NYC DOT) (New York City Department of Transport). The results are shown in the next section Section 4.

3.3.Speed-distributioncurves

We explore the distribution of mean segment speeds in the Ubermovements dataset by plotting the cumulative distribution of speedtime series. Given the hourly speed data in a road segment over aperiod of time, we first sample the speed time series using a Poissondistribution with .. =8 to remove temporal correlation effects in the speed data. The value of .. was chosen based on the length of observedregions of low-speeds (or jams). Then we plot a distribution of all themeasured/observed average vehicle speeds as a cumulative density,which shows the distribution of speeds across all the segments observedover the entire time period of two years. For well-behaved segmentsshown in Fig. 6, which make up almost 90% of all segments, we obtainan S-shaped curve, while for the remaining segments, as shown inFig. 7, we see irregular shapes.

For the well-behaved segments, it is clear that there are two turningpoints, which show significant transitions in the traffic behavior of thesegment. To obtain the corresponding values of speeds for these points,we fit a 3-way piecewise linear function to this CDF using the pwlflibrary in Python (Jekel and Venter, 2019) to obtain the two break points, ..1 and ..2, such that ..1 < ..2. Well-behaved segments havetwo clear break-points while the remaining segments don t have clearbreak-points.

Fig. 8 shows the distribution of the minimum, maximum, ..1, and ..2 speeds for all the valid segments for Nairobi, New York City, andS o Paulo. We note that the median value of ..1 is about 20 kph acrossall three cities. This is an interesting observation, given that the otherthree quantities show significant differences across the three cities. Inthe next section, we hypothesize that ..1 value of a segment correspondsto an important phase-transition point in the traffic curve. This mightbe the reason why we get similar values of ..1 across all cities.

3.4.Estimatingtrafficcurves

In practice, sudden jams happen over very short timescales, such aswithin 5 min (Jain et al., 2012), and we might not always have speedor density data at that fine granularity in order to be able to analyzethem. In such situations, we cannot apply the formula from Eq. (1). Additionally, we might not have information about the actual vehicledensity on the road. In such cases, under the framework of certainassumptions, we can estimate the traffic curve from the speed dataalone, from which we can identify key threshold points for determiningsudden jams.

Now we describe a methodology to compute the traffic curve, as in Fig. 4, from observed hourly speed data. We begin by dividing thetraffic curve into three different regions based on our observations inmean-speed distributions, namely the free-flow region, the spiralingregion, and the jam region. The free-flow region of the traffic curverepresents a constant flow under equilibrium, which is only possiblebefore the optimal buffer capacity (..\*) as shown in Fig. 4. The spiraling

..

region of the traffic curve represents the phase after the optimal buffercapacity has been crossed and when the exit rate of the link rapidlydrops. The spiraling region ultimately leads to the final region ofthe traffic curve, the jam region where entire traffic is brought to astandstill and moves forward at a very small constant speed. Fig. 9provides an illustration of these regions. We make a few assumptionsfor simplistic modeling.

Fig.9.Dividing the traffic curve into different regions based on traffic behavior. Thefree-flow region corresponds to equilibrium traffic where the link can maintain free-flow traffic before the optimal buffer capacity. The spiraling region corresponds to therapid drop in exit rate with increasing buffer capacity, which ultimately leads to trafficcollapse, leading to the jam region of the traffic curve.

First, we focus on the free-flow region of the traffic curve. Basedon common knowledge in written driving tests (Driving Test Success),drivers are required to maintain a certain stopping distance with vehi cles in front of them, which consists of two components, the thinkingdistance, and the braking distance. The thinking distance is based onthe human reaction time and is linear with the speed of the vehiclewhile the braking distance is the distance it takes for the brakes to bringthe vehicle to stop, which is quadratic with respect to the speed of thevehicle. Thus, the stopping distance can be expressed as:

..(..)= .. ..+ .. ' ..2 (2)

where .. represents the human reaction time threshold while .. ' is the corresponding constant for the quadratic term, and .. is the speed ofthe vehicle. It should be noted that the above relationship betweeninter-car distance and vehicle speed should be largely accurate for thelow buffer-density phase of the traffic curve. Based on (Driving Test Success), the values for .. and .. ' should be 0.675 and 0.076 respectively.Traffic mismanagement and chaotic driving conditions are likely tocause these values to be lower than the recommended values.

Now, let us assume an infinite road segment constrained underprevious assumptions, filled with cars maintaining a constant speed s.In this case, the buffer density of the link would be:

.... ....

..(..)= = (3)

.... + ..(..) .... + .. ..+ .. ' ..2 where .. is the stopping distance and .... is the length of each car. Forsimplicity, we assume all cars are of equal length .... =4 m. At the same time, we have the following relations between exit rate, buffer densityand speed in the segment:

.. ..

..(..)= ..(..) .. . ..(..)= = (4)

.... .... + ..(..) .... + .. ..+ .. ' ..2

Eqs. (3) and (4) give us a parametric relationship between buffercapacity and exit rate, which is valid for the low-density phase of thetraffic curve. Now, let us consider the other extreme phase of the trafficcurve, the jam region.

The jamdensityis the upper limit on free-flowing traffic density,beyond which the road segment is said to be in the state of a jam (May,1990). Although there is a bit of variation on this threshold density inliterature (Knoop and Daamen, 2017; Wu, 2002), the theory according to May (1990) gives a value for jam density of 185 to 210 vehiclesper kilometer per lane, which translates to between 74% and 84% laneoccupancy, assuming an average car length of 4 m. We assume thethreshold for a jam to be 66% occupancy of the road segment. This corresponds to a spacing of half a car between every two cars. Webelieve that such a small distance between vehicles is enough to bringthe traffic to a stand-still.

From the jam point onward, the relationship between buffer capac ity and exit rate no longer follows the parametric Eqs. (3) and (4). For deriving a relationship between the two entities, we consider the casewhere the cars are packed in the road segment with inter-car spacingD and the traffic is at standstill. Say that after this particular roadsegment, we cross the choke point and the traffic resumes its free flowstate. An example of such a situation could be a smaller road merginginto an express highway. In this case, say that .. cars are able to exit the road segment in time duration T. Then, the exit rate ..0 is given by .. . Now, consider the case when the inter-car spacing is reduced by

..a small amount ..... Then, the buffer capacity of the new situation is

given by:

..(....)= .... (5)

.... + ..- ....

Also, due to the cars having lesser inter-car spacing, each car mustwait an additional time .... before it can accelerate to the speed of thecar in front of it. But, it should be noted that this additional time keepsgetting accumulated for each car since the second car must wait .... for the first car before accelerating, while the third car must wait .... for the second car, and so on. Therefore, the time taken for .. cars to cross the choke point will be ..+.. ..... Therefore, the exit rate, in this case, would be:

..

..(....)= (6)

.. + .. ....

Now, we consider the lowest of the traffic corresponding to the jamexit rate ..0 as ... In that case, we have the following relation:

.... = .. ....

Following the parametric forms in Eqs. (3) and (4), we have:

.. .... .. ..

..0= . = . .. =

.... + .. .. .... + .. .... + ..

Then, substituting the above-obtained value of .. in Eq. (6), we get:

.. .. ..

..(....)= . ..(....)= (.... + ..) (.. + ........ ) .... + ..+ .. ....

....+..

Now, we use the relationship between .... and .... in the above equation. Thus, we have:

..

..(....)= (7)

.... + ..+ ....

Eqs. (5) and (7) give a parametric relationship between buffercapacity and exit rate for the high buffer density or jam-phase ofthe traffic curve. Thus, we have two different parametric forms ofrelationship between exit rate and buffer capacity in three differentregions, namely the free-flow and jam regions, of the traffic curve. Inthe spiraling region lying in between the two regions, the dynamics ofthe exit rate and buffer capacity are non-trivially related and hard todeduce. As we saw in Section 3.3, the mean segment speed distributions show clear break points at ..1 and ..2, where for speeds lower than ..1,we observe rapidly decreasing values of mean segment speeds, showingthe relationship between ..1 and traffic collapse. Thus, we hypothesizethat the free-flow region of the traffic curve transitions to the spiralingregion around the ..1 speed value for a given segment. This gives us thephase-transition point between the free-flow and the spiraling phases ofthe traffic curve. The spiraling phase would then smoothly join into thejam phase of the traffic curve. We assume that the jam phase starts at ..0=0.66 and the corresponding speed of traffic at this point (i.e. ..) is

3.6 km/h (1 m/s). Then, we use parabolic curve fitting and smoothingto complete a continuous and differentiable transition between the tworegions of the traffic curve and obtain the complete traffic curve asgiven in Fig. 10 for different segments.

3.5.Suddenjamsinhourlyresolution

In reality, the perception of a jam would depend on the particularroad segment. On a highway, where speed limits may normally beupwards of 100 kph, drivers may perceive the state of driving at lessthan, say even 40 kph, to be in a state of a jam. Whereas on a city road,the limit is much lower.

We observe two inflection points in the speed distribution (..1 and ..2), where there is a sudden change in the gradient. We also note thatthe median speed of the segment is close to ..1+..2 . Another observation

2is that ..2 = 3 ..1 with high probability. Based on this, we heuristically

define traffic jams (called slowdown jams) as instances of time when

..1+..2

the value of mean segment speed falls below . Since we see a

4sudden drop in speeds below ..1 and ..1+..2 <..1 with high probability, we

4

choose this as the threshold for our definition. Note that other values of the threshold can be chosen with similar justifications.

For understanding, if there is a correlation between sudden jamsand showdown jams, we generate the hourly resolution of a section ofthe NYCDOT dataset by averaging the speeds reported over a segmentfor each hour. Note that this method of generating hourly resolutionis inaccurate because we don t have data about the density of cars inthe given links. Also, we see that in hourly resolution data obtained bythis process, most segments don t behave well , in that they don t haveclear breakpoints. Still, we proceed to apply the definition of slowdownjams on the hourly resolution of the NYCDOT data to compute theoccurrences of slowdown jams. After this, for each occurrence of aslowdown jam, we take a look at the observations that make up thehourly average and check if we observe a sudden jam based on thedefinition given in Eq. (1). Taking the recent 2 million observationsfrom the NYCDOT data, we find that in 67.38%of the cases where we observe a slowdown jam, we can see a sudden jam appearing inthe corresponding hour. Note that this happens even for ill-behaved segments, hence, we can safely assume that the occurrence of slowdownjams, in reality, should be strongly correlated with sudden jams inreality.

4.Results

4.1.SuddenjamsinNYCDOTdataset

When characterizing sudden jams, signals with average reportingrates of 90 seconds or less were used. Further, segments had to havea polyline component. These two conditions reduced the total set of153 segments to 98. Finally, to be eligible for jam classification, theobservation and prediction components of a given window cannotcontain missing data.

Recall that a window consists of three components observation,prediction, and target. A window is considered a sudden traffic jamif the average speed between the observation and target portionsdecreases by more than a particular rate. Prediction window is thusthe time between the observation and target portions. Fig. 11 presentsan overview of frequency using a fixed .. = -0.002, and window sizes varying from 1 to 10 min. The two window portions observation and target remained equal throughout. As such, they are denotedsimply as adjacent. The frequency of sudden jams depends not onlyon the characteristics of the segment but on parameters to Eq. (1); in particular, the size of the window and the choice of ...

Fig. 11(a) outlines the inverse relationship between sudden jamfrequency and respective window sizes on a sample segment. Predictionwindows range from 0 to 10, where 0 signifies a comparison betweenadjacent points in time. The adjacent windows range from 1 to 10, asa lower bound of 0 would mean a comparison between non-existentwindows. Darker cells denote higher occurrences, with each cell an notated with the number of occurrences. The number of sudden jamsincreases as the size of the adjacent window increases and as the size of

Fig.10.Empirically derived traffic curves for four different road segments with their open street map way id given in figure titles. As can be seen, the first phase transition pointlies close to the values of exit rate and buffer capacity given by ..1 according to Eqs. (3) and (4). The second transition point is fixed on the traffic curve based on our assumptions.

Fig.11.Sudden jam characterization across all segments in the network.

the prediction window decreases. The increase across prediction win dows is exponential, while the increase across the adjacent windows islinear. With respect to the adjacent windows, this relationship is likelydue to variability in average speed. Using observation and predictionwindows of size one means that the model is taking into consideration unsmoothed values. In some cases, these observations may not beentirely representative of actual conditions; a result of measurementanomalies, for example. As window sizes increase, spurious values canaugment average speed such that a sudden jam is harder to determine.With respect to prediction windows, the inverse relationship is largelya result of the manner in which sudden traffic is calculated: largerprediction windows require a larger decrease in speed between theobserved and target windows to be classified as traffic events.

Fig. 11(b) presents the average standard deviation at varying adja cent window sizes across all segments considered. The large number of traffic incidents shown in Fig. 11(a) for smaller adjacent windowsegments is dominated by a relatively small number of road segments.Measurements across mid to large windows, while less in number, arespread more evenly.

4.2.SlowdownjamsinUbermovementsdataset

..1+..2

We apply the threshold on every one of the valid segments

4

in all three cities. We observe the statistics for the slowdown jams inthe three cities as shown in Table 1. From the table, it is clear that the average jam time per segment per day for Nairobi is outrageouslyhigher than (almost 3x) the same for New York City and S o Paulo.

We present the histogram distribution of the time of jams occurring in Fig. 12 and of the duration of jams in Fig. 13. From Fig. 12, we

Table1

Jam statistics for slowdown jams across all three cities. We present the number of segments, the number of valid segments with sufficient datapoints, the number of slowdown jams observed, the total hours across all jams, and the mean amount of time spent in jams for each segmenteach day in hours.

City Segments Valid segments Jams Total jam hours Mean jam time

Nairobi 4949 3063 3930954 4753618 1.89

New York 35602 25371 8400572 14033002 0.67

S o Paulo 89121 53658 20091200 29340467 0.67

Table2

Sample of 9 segments from the 6 junctions, showing total hours in jams, the number jams observed, the mean hours per day spent in jams, the mode hours (most commonlyobserved jam duration), and the mode hour of the day (most commonly observed time of day when jams occur).

Way ID Total hours in jams Number of jams Mean hours in a jam Mode hours in a jam Mode hour of day

9931279 1453 1453 1.77 1.0 05:00

678371493 865 334 1.05 2.0 13:00

364279376 643 219 0.78 2.0 13:00

678371494 658 259 0.80 2.0 13:00

4724017 2763 2763 3.37 1.0 12:00

336067605 3303 3303 4.02 1.0 15:00

39573541 405 162 0.49 2.0 11:00

580233744 4092 4082 4.92 1.0 14:00

4742016 4794 4794 5.84 1.0 14:00

observe that the jam time patterns for S o Paulo and New York Citymatch each other largely, with both cities suffering congestion duringlate night hours while Nairobi presents an inverted case with most ofthe congestion occurring during afternoon hours. In Fig. 13, we observethat for all three cities, most jams last only one hour. This refers to thepattern of finding only one entry in the speed time series to be less thanthe threshold surrounded by entries that are larger than the threshold.

4.3.Investigatingimportantjunctions

Table 2 shows statistics for six representative junctions in the cityof Nairobi, covering a variety of settings T-junctions in the city, highway merges and roundabouts, and Figs. 14 to 15 show some samplesnapshots for the six segments on various days. The faint lines show theinput segments into the output segment(s) of interest, which are shownwith thicker lines. The red color shows a jam, which is when the speed

..1+..2

in a segment drops below the for that segment. The snapshots

4

show how the average speeds in the segments vary over the course ofthe day.3 We note a large number of instances of prolonged congestion

(i.e. jam) in the sink segment in junctions B, D, and E. In the roundaboutjunctions C and F, we observe jams at one or two output sink segments.We observe that in many cases, the jams persist for over 2 to 3 h. In thejunctions B, D, and E particularly, which are all 2 1 merges, we observethat the average speed in the output segment is below the respectivethreshold continuously for more than several hours on multiple days.

4.4.Traveltimeimpact

For an individual segment of fixed length, the travel time for thesegment and the mean speed are expected to follow an inverselyproportional relation. We validated this assumption for the NYCDOTdataset by computing the product of travel time and mean speed forall entries of particular segments, and computing the coefficient ofvariation of these products. The coefficient of variation equals the ratioof standard deviation to the mean of the data, and a value of less thanone is considered to be a small variation in data. Given that we expect

3 For the sake of brevity, we only show handpicked snapshots for each ofthe junctions that best illustrate the different phases. We will be happy toshare our analyzed data in greater detail as needed for the reproduction ofour results.

the product to remain constant, our threshold for the coefficient ofvariation should be much smaller. In practice, we obtained a value ofless than 0.1for all road segments in the NYCDOT dataset except 2outliers, with most segments having values in the range of ~0.01. Thus, we can assume for individual segments:

1

............ ........ . ........ ..........

Under jam conditions, the average segment speed can fall down to5 km/h for a segment with an operational speed of 50 km/h, meaningthat the travel time for jammed segments can see up to 10x increase.Depending on the source and destination as well as the commute pathtaken, the impact of jams on travel time will be variable. In the Ubermovements dataset, we find the travel time data for cities of Nairobi and S o Paulo between source and destination hex-clusters averagedby hour buckets per day from January 2020 to March 2020. Due todifferences in resolution from speed data as well as lacking data on thecommute path between the clusters, we have been unable to join thetravel time data with the speed data to understand the impact of jamson travel time with high granularity. Still, we compared the maximumobserved mean travel time on the segments to the average of the meantravel time. The results are shown in Fig. 16. We observe that for a majority of source destination pairs, the travel time in a jam can bemore than 50% of the average travel time. For a smaller fraction ofcases, the jam can cause the travel time to increase by 3x or higher.

5.Discussionandconclusion

In this paper, we have presented the concept of sudden traffic jams,with a formal definition, the methodology to detect such jams and thecorresponding theoretical foundation. It should be noted that suddentraffic jams are not a phenomenon emerging due to over-subscriptionof traffic flow but rather due to momentary bursts in the traffic. In ouranalysis, we found that highways and other free-flow segments are alsosusceptible to the phenomenon. Based on the comparisons between thethree cities of New York, Nairobi, and S o Paulo, we have determined that the city of Nairobi experiences unexpectedly higher severity ofjams as compared to the other two cities.

Table 3 presents some key development indicators of the three citiesincluding the population, percentage of households that own a car,number of segments in the Uber Movements dataset, and the mean jam

Fig.14.Junctions A through C. On the left, we have maps with arrows showing the direction of traffic flow. On the right, we see the speeds observed in different segments.Faint lines represent in-flow traffic while thick lines represent out-flow traffic. Red is used to represent speeds below the threshold. (For interpretation of the references to colorin this figure legend, the reader is referred to the web version of this article.)

Table3

Development statistics all three cities where we present the number of segments observed in Uber Movements data, the population based on

recent surveys, percentage of households owning motor vehicles (cars), the mean amount of time spent in jams for each segment each day in

hours and the average number of vehicles per segment.

Source:NYCEDC, Wambu, EMBARQ Network.

City Segments Population Household-vehicle Mean jam time Mean traffic load

percentage

Nairobi 4949 4.4 M 16.9% 1.89 37.56

New York 35602 8.4 M 45% 0.67 26.54

S o Paulo 89121 12.33 M 40% 0.67 13.84

to this. As described in Section 3.1, the phenomenon of sudden jamsproblem. Consider the empirical formulation of traffic curve presentedemerges from the traffic collapse resulting from the decreasing linkin Section 3.4. Based on our observations from speed-distributionscapacity in the spiraling region of the traffic curve. We now showshown in Section 3.3, we hypothesize that the traffic curve shifts fromhow an aggressive driving culture can exacerbate the traffic congestion the free-flow phase to the spiraling phase at segment speeds around the

Fig.15.Junctions D through F. Again, we have maps on the left and speed profiles on the right. Faint lines represent in-flow traffic while thick lines represent out-flow traffic.

Red is used to represent speeds below the threshold. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig.16.Travel time blow up for different source destination pairs in Nairobi and Sao Paulo. In more than 50% of such pairs, we find an increase in travel time of more than 50%.

Fig.17.Traffic curves for aggressive and safe driving behavior. It can be seen that thetransition point from the free-flow to the spiraling region in the curve moves diagonallyupwards, leading to a higher downward slope in the spiraling region for the aggressive curve.

value of ..1, or the first break point in the speed distribution. The pointon traffic curve corresponding to this can be found by substituting swith ..1 in Eqs. (3) and (4) as follows:

......(..1) = .... + ....1+ .. ' ..2

1

..1 (8) ..(..1) =

.... + ....1+ .. ' ..2

1

For aggressive driving behavior, we would consider smaller valuesof t and t . This would result in a higher value for both ..(..1) and ..(..1),meaning that the point on the traffic curve will shift to the right andup. Note that the second transition point on the curve is fixed, andhence after curve fitting, we will obtain a higher downward slope inthe second case (see Fig. 17). A higher slope in the spiraling region ofthe traffic curve can lead to more frequent and rapidly evolving jams,causing a larger duration of jam-time.

How do we mitigate these jams? Obviously, the development of theroad infrastructure will help the problem to a large extent, as in the caseof S o Paulo, but it comes at a significant economic cost. Hence, weask: is there a smarter way of traffic management that can increase theutilization of existing road infrastructure? Again, turning to the trafficcurve from Section 3.1, the key idea is to be aware of the jam densityand the threshold speed in a segment. Real-time instrumentation, suchas the one in New York City, can inform drivers through navigationapps about impending congestion in a segment. Such knowledge canalso be used in signaling at important points such as ..-1 merges, wherewe observe the most instances of congestion resulting in prolongedjams. We believe designing such solutions will greatly benefit the de veloping cities around the world, which are disproportionately affectedby the problem of traffic congestion.

Thus, to conclude, the key takeaways from our work are the col lections of observations about traffic jams they can appear in variousscenarios, for various durations, and can potentially result in prolongedcongestion of vehicles on the road, on many occasions lasting severalhours at a stretch. Sudden jams that appear due to an increase in vehicledensity beyond the threshold jamdensityare particular types of jamsthat last for long periods of time. We have provided a traffic curveformalism for understanding the phenomena of traffic collapse leadingup to sudden jams, and a formula for sudden jams in terms of the dropin acceleration. For more sparse data such as in the Uber movementsdataset, where we do not have minute-on-minute data to use theformula, we have proposed an alternative approach to estimating thetraffic curve from the speed data and some basic assumptions. Wecompute an upper limit on the speed at the jam density in a road segment from the speed distribution using two break points ..1 and ..2 in the cumulative distribution of speeds and call these jams as slowdown jams. Using the loop detector data from the New York City Departmentof Transportation, we show that slowdown jams and sudden jams havea high correlation. Applying the hourly definition to Uber movementsspeed data, we see that the city of Nairobi experiences unexpectedlyhigh severity of traffic jams as compared to New York City or S oPaulo, cities representative of the developed and developing economies.We attribute some part of this result to chaotic driving conditions andtraffic mismanagement and propose that designing smart solutions forincreasing road capacity utilization based on our work would reducethe economic budget for tackling the problem.

Declarationofcompetinginterest

The authors declare the following financial interests/personal rela tionships which may be considered as potential competing interests:Shiva R Iyer reports financial support was provided by NYUWIRE LESS Industry Affiliates. Lakshminarayanan Subramanian reports a re lationship with Velai Inc that includes: equity or stocks. Lakshmi narayanan Subramanian reports a relationship with Gaius NetworksInc that includes: board membership and equity or stocks. Lakshmi narayanan Subramanian reports a relationship with Entrupy Inc thatincludes: board membership and equity or stocks. LakshminarayananSubramanian reports a relationship with World Bank Group that in cludes: consulting or advisory. Lakshminarayanan Subramanian reportsa relationship with The Governance Lab that includes: consulting oradvisory.

Dataavailability

The data used is available in public domain and the correspondinglinks have been cited in the manuscript.

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