A STUDY OF ALTERNATIVE FOR RIGHT-TURNING MOVEMENT AND REAL-TIME TRAFFIC ANALYSIS SYSTEM

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Abstract— Due to the current significant increase in population and, consequently, to traffic congestion in most of the world's metropolitan cities, the design of an intelligent traffic management system (ITMS) to detect the road in the shortest possible time. Travel is critical for emergency, health, and courier services. The objective of this thesis study was to develop a theoretical traffic detection system capable of estimating the travel time associated with each segment of the street based on the traffic data updated every 20 seconds, which successively finds the way with Shortest travel time on the net by using a dynamic programming technique. In addition, in this study, we modeled the travel time associated with each street segment based on historical and real-time data, considering that the speed of traffic on each road segment is constant by parts. It would be useful to implement such algorithms in GIS systems, such as Google map, so that service drivers can avoid congested routes when receiving traffic information in real time. Consequently, we design a map-matching algorithm that processes erroneous vehicle location data collected using cellular network to generate vehicle trajectories. The vehicle trajectories are used to compute edge-level vehicle flow, space occupancy, and congestion level data. The simulation results show the feasibility of accurate estimation of the traffic parameters in real time. We observe the need of additional accurate data sources for edge level speed estimation in the whole road network.

1. INTRODUCTION

Road transport is the primary mode of transport in India which plays an important role in conveyance of goods and passengers and linking the centers of production, consumption and distribution. As per 2007-08 reports, the road network carries more than 56% of total freight traffic in the country.

The sustained economic growth, increasing disposable income, and rising urbanization has led to rising demand for road transport and personalized mode of transport (cars and two-wheelers), in particular. The total number of registered motor vehicles has increased from 55 million in 2001 to 141.8 million in 2011 at a growth rate of 9.9%. On the other hand, the road network in the country has developed at a rate of 3.4% during the same period. The vehicle population has grown three times faster than the road network during the period. Even though the road network density in India (1.42 km/square km) compares favorably with many countries, the road network growth could not cope up with the explosive growth in vehicle population.

The share of two-wheelers in the overall vehicle population has increased from 8.8% in year 1951 to about 72% in the year 2011. On the other hand, the fraction of mass transit buses has reduced from 11% in year 1951 to 1.1% in the year 2011. The limited availability of mass transit and a significant increase in affordable two-wheelers, along with limited road infrastructure, are the major reasons of increasing traffic congestion in India.

Congestion wastes a massive amount of time, fuel and money. As per the urban mobility report, 2011, congestion is a significant problem in America's 439 urban areas. In 2011, a billion gallons of fuel was wasted (equivalent to about 2 months of flow in the Alaska Pipeline) and 4.8 billion hours of extra time was spent in vehicles (equivalent to the time Americans spend relaxing and thinking in 10 weeks) due to congestion in these areas. This resulted in $101 billion of delay and fuel cost (the negative effect of uncertain or longer delivery times, missed meetings, business relocation and other congestion related effects are not included). The cost to the average commuter was $713 in 2010 compared to an inflation-adjusted $301 in 1982.

An Intelligent Transportation System (ITS) uses electronics, communication, and information technology to improve efficiency and safety of the surface transportation. The broad application areas of ITS are as listed below:

- Advanced Traffic Management System (ATMS): The ATMS uses real-time traffic information to predict traffic congestion or detect incidents in a road network to improve the efficiency of traffic movement. The traffic information may be used to control the cycle time of adaptive traffic lights, enforce diversions or suggest alternate routes (to avoid the incident region).

- Advanced Traveler Information System (ATIS): The ATIS aims to provide real time traffic information (location of incident, optimal route for a trip, road conditions, lane restrictions, etc.) to travelers in real time to enable choice of travel mode, planning of a trip or to make rerouting decisions during a trip.

- Advanced Vehicle Control System (AVCS): The AVCS is an in-vehicle technology that aims to enhance the driver's control of a vehicle to make travel safer and efficient. It includes collision or lane departure warning systems, an automatic braking system, etc. The autonomous vehicles (e.g. driverless cars) represent the latest advancement in the category.

OBJECTIVES

- To generate an accurate estimation of edge-level traffic information in real time and examine its utility.

- To design the ITS infrastructure deployment models and evaluate them for infrastructure requirements, feasibility of incremental deployment and fault tolerance.

- To design and validate a distributed processing and communication framework for the proposed ITS to assess the feasibility of large-scale deployment.

II LITERATURE REVIEW

Valerio et al. analyze mobile hand off related cellular network signaling data to generate road traffic information. They make the following observations: (1) cellular signaling pattern is different on week days and weekends; (2) cellular signaling pattern is different at different times of a day; (3) train users generate different cellular signaling pattern than car users; (4) in an event of incidence, the signaling notch (high decrease) followed by a peak occurs. This clearly indicates that the cellular user classification using hand off or other cellular signaling data is possible.

Bar-Gera processed cellular data of handover events collected on 14km of Ayalon freeway in Israel with 10 interchanges in both directions during January-March 2005 to estimate travel times. The cellular-based system received observations for about 1-3% of the total traffic during daytime (1000-2000 hrs) and generated 63% valid travel time estimates for 27 road segments. Cellular data was noisier (14%) than loop detector data (5%). The noise was measured as the average absolute relative difference between travel time estimates for consecutive five-minute intervals. However, the algorithms used for map matching and travel time estimation are not described in the work.

Calabrese et al. used cellular signaling information available at A_{bis} interface (handover) and *A*-interface (location area updates) in the city of Rome. A_{bis} signaling data was processed in real time to predict user terminals' position and speed to produce the traffic map. Received signal power (RXLEV and RXQUAL) and Time Advance (TA) value were used to estimate the location of active terminals. The location error of 159 meters in urban areas, 295 meters in suburban areas, and up to 1457m in the extra urban area were reported. The error in considering moving user as still and vice-versa was only 3.2%. The travel time estimation error when compared to the readings taken using GPS and odometer was 14.88% on bypass roads, 10.08% on primary urban streets, and 17.66% on secondary urban streets. The *A* interface signaling was used to generate coercive grain location information about active or idle users using location area updates.

Traffic Online, Vodafone, analyzed signaling information on *A* interface and A_{bis} interface to generate traffic information. They claim to generate high-quality traffic information without mentioning the methods or algorithms used in signal processing.

Liou et al. compute cell residence time and edge-level speed using sparse cellular handover data. They propose the LinChangHuangfu (LCH) scheme and evaluate its performance for speed estimation on National Highway 3 in Taiwan. To improve the accuracy of speed estimation, the road segment filtering (using location area information) and historical vehicle traces are used. The cellular data of a fifteen-minute period is aggregated for speed estimation. After bias removal, the mean discrepancy between the cellular-based speed estimation and loop detector data is 7.51%.

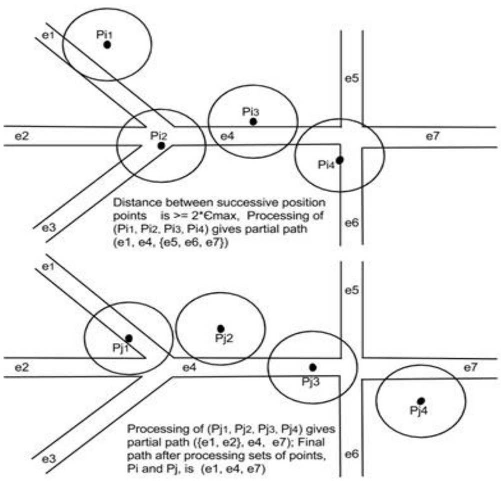
Demissie et al. use cellular handover data to generate non-real-time traffic state information. The study shows that there is a correlation between the traffic volume on a road segment and the count of handovers in the corresponding cell (a correlation coefficient of 0.76 is reported). The solution uses Multinomial logit and Artificial Neural Network (ANN) to relate the sparse data of handover to the traffic state on arterial roads. The performance of the proposed methodology is evaluated using five case study areas of Lisbon city, Portugal. The accuracy of 78.1% is achieved in traffic state estimation.

Caceres et al. observe that if the cell boundary or location area boundary is precisely known, the number of vehicles crossing that boundary can be counted just by counting the number of hand overs (considering the percentage of users making a call at a given time). This can be used as an induction loop detector, counting number of vehicles crossing it, provided the cell is sectored and cell boundary or sector boundary maps to a unique road segment. However the assumption made in the paper, i.e.

cell boundary or location area boundary is precisely known and it maps to a unique road segment, is very unrealistic.
Cayford et al. at Institute of Transportation Studies, Berkeley conducted a study to evaluate effect of location accuracy, frequency of location measurements, and number of locations monitored, on traffic information generation using cellular network [15]. With location error of 100 meters, a vehicle could be mapped to a correct road for 98.4% of all surface streets and 98.9% of all free ways. With the update frequency of 30 seconds (preferred by all the cellular carriers) and location accuracy of 50 meters, 98.8% of the road segments could be identified. As the number of locations increases from 1 per second per square mile to 10 per second per square mile, the percentage of roads covered increases very rapidly. Above 20 locations per second per square mile, the increase in the percentage of roads covered declines, and there is little benefit of using more than 40 locations per second per square mile. With network-based location technology, the measurements of 85% of the roads can be generated in every five minutes interval using approximately 5% location capacity of a cellular carrier. Operating continuously, the traffic information approaches 97.7% of the road segments, the maximum possible with a location technology accurate up to 100m using 30 seconds update frequency. The similar results are observed in handset-based location technology. The authors did not consider location errors larger than 100 meters. The algorithms used for map matching and traffic estimation are not mentioned in the paper.

III PROPOSED APPROACH

To assess location error in the cellular network, we use fingerprinting-based localization. The reason for using this technique is that it does not require access to the cellular infrastructure elements and is viable using any GPS-enabled smartphone. An Android application was developed to collect cellular fingerprint (main cell ID and RSSI value, neighbor cells and RSSI values) and corresponding GPS coordinates every second.



Functioning of the Map Matching Algorithm

Algorithm : Map Matching Algorithm

Input: road network topology, series of position estimates for a vehicle taken every 30 seconds, maximum position error s_{max}

Output: estimated path of a vehicle

1: Let $P = (P_1, P_2, \dots, P_n)$ be a series of position estimates of a vehicle recorded at time $T = (t_1, t_2, \dots, t_n)$, respectively, where $t_{i+1} = t_i + 30$ seconds, $\forall i < n$.

2: **for all** $P_i \in P$ **do**

3: Let E_i be the set of edges overlapping with a circle centered at P_i and having radius s_{max}. E_i contains all the edges the vehicle may be traversing at time t_i. Each $e \in E_i$ is of the form $[ID, position]$, where, ID is a unique identifier of the edge and $position = (x_1, y_1, x_2, y_2)$ represents end points of overlapping region of the edge.

After examining location error in the cellular network, a map matching algorithm is developed that processes the location estimates of a vehicle generated using the cellular network to compute the vehicle trajectory. The map matching process is described in Algorithm 3.2. Due to a large location error, it is not possible to determine a correct edge or correct movement direction of a vehicle using single location point. Hence, a series of location points are processed to get the direction of vehicle movement. Instead of mapping the vehicle to a particular edge, we map it to a set of edges and then try to filter out some of the improbable edges using antecedent or subsequent position estimates. This mechanism works well except for the location points towards the beginning or end of the trip. Due to the absence of appropriate antecedent or subsequent position estimates in these cases, it becomes difficult to determine exact edges. Specifically, it is difficult to predict whether a vehicle took a U-turn at the beginning or end of its journey. Such cases are not taken care of by the map matching algorithm and it is assumed that a vehicle does not take U-turn at the beginning or end of its trip. However, this assumption leads to the prediction of a truncated path when a vehicle actually takes U-turn at the beginning or end of its trip.
Figure shows functioning of the map matching algorithm. A location point along with three subsequent location points, separated by at least $2 \times s_{max}$ from one another, is processed to estimate partial path traversed by a vehicle. This adds some amount of
overlapped processing of location estimates and gives overlapping partial path. A unique partial path estimation is computed by considering only common edges which are part of all the predicted partial paths. This assures the correct edge selection independent of the amount of location error. The complete path of a vehicle trip is estimated by concatenating the overlapping partial paths.

Removing Time Lag in Traffic Data

As the map matching algorithm needs to process a series of erroneous position points before associating a vehicle to an edge, the vehicle flow and space occupancy have a time lag of about one aggregation period, and can not be used in a real time traffic information system. To overcome the above limitation, temporal extrapolation of vehicle count and flow data is required.

Various statistical methods for time series forecasting (exponential moving average, Box-Jenkins, regression, etc.) are compared in [60] and shown that the exponential moving average gives a reasonably good short-range forecast with the least computation and storage requirement. Also, machine learning techniques such as regression, artificial neural network, genetic algorithm, etc., are used successfully in literature for temporal extrapolation [61]. The machine learning techniques have higher storage requirements in general as they use historical data for learning model parameters. The regression-based models are the simplest among machine learning techniques and have the least computation requirement.

Considering the real-time processing requirement of vehicle count and flow data, we choose the simplest and least computation-intensive methods from each category, namely,

exponential moving average and (2) polynomial regression, for temporal extrapolation of traffic data

IV DISTRIBUTED PROCESSING

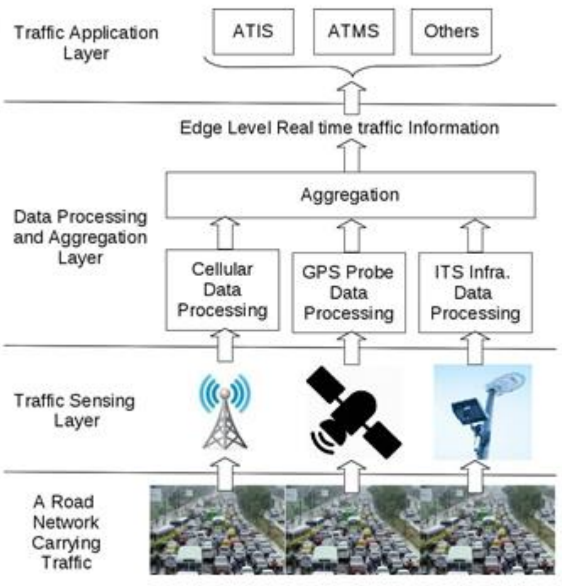


Fig.: Multi-modal Intelligent

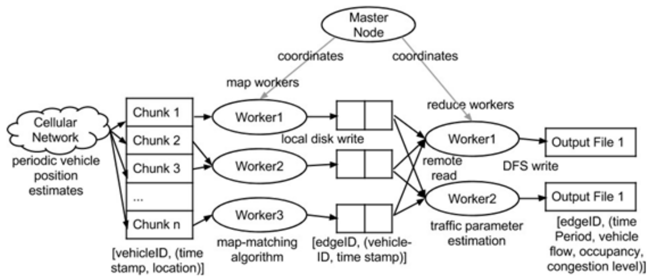
Transportation System The details about various functional components of the proposed Intelligent Transportation System (ITS) are discussed. Figure shows a block diagram of the resulting multi-modal ITS. The Traffic Sensing Layer uses cellular network, GPS probes and ITS infrastructure for generating raw traffic data. The cellular network tracks all the vehicles using active signaling and generates erroneous position data periodically. The GPS probes report their accurate positions periodically. The ITS infrastructure deployed using the Congestion Coverage Model (COCOMO) or Edge Coverage Model (ECOMO) reports edge-level speed estimation periodically for all the infrastructure edges.

The MapReduce Framework

The MapReduce framework proposed by Google provides an abstraction layer to design and implement programs for execution on a large cluster of commodity machines. The input data set is specified as key-value pairs. The programmer defines a map function and a reduce function for a distributed application. The map function processes a unit data element (a key-value pair) to generate a set of intermediate key-value pairs. The reduce function aggregates intermediate values associated with an intermediate key to compute the final result. The programs written in this manner are parallelized automatically and the run-time system takes care of parallelization, fault tolerance, data distribution and load balancing.

CellularDataProcessingusingMapReduceFramework

The framework takes as input the periodic position updates of all the vehicles and computes vehicle flow, space occupancy and congestion level data for every edge. The figure shows a functional block diagram of the cellular data processing using the MapReduce framework.



Cellular Data Processing using MapReduce Framework

Result and Observation of test carried out in previous chapter is presented, analyzed and discuss. This chapter is divided into five sections. First section is deals with parameter used for analysis. Second section deals with calculation of Optimum binder Content (OBC) of BC where cement, fly ash, stone dust is used as filler. Third section deals with calculation of Optimum binder Content (OBC) and Optimum Fibre content (OFC), Marshall Properties of BC with or without using fibre. Fourth section deals with calculation of Optimum binder Content (OBC) and Optimum Fibre content (OFC), Marshall Properties of SMA with or without using fibre. Fifth section deals with result of Drain down test and Static Indirect Tensile Stress and static Creep test.

GPS Data Processing using MapReduceFrame- work

The GPS probe vehicles report their position updates periodically which are processed to compute edge level GPS probe speed. The COCOMO and ECOMO do not use the GPS probe speed data in real time. Instead, the

average GPS probe speed is computed for all the edges and congestion levels using data collected over few days period (section 3.4). As the processing of GPS probe data is a non-real time task, it can be carried out when the load is less in the system, e.g. during off peak hours.
It is assumed that periodic position updates of GPS probes are available in the form of [vehicleID, (time stamp, location)] pair. The information is stored in DFS and is accessible to all the nodes. The GPS probe trajectory generation is associated with the map function and the average GPS probe speed computation is associated with the reduce function. The MapReduce processing of GPS probe data is elaborated in the following:

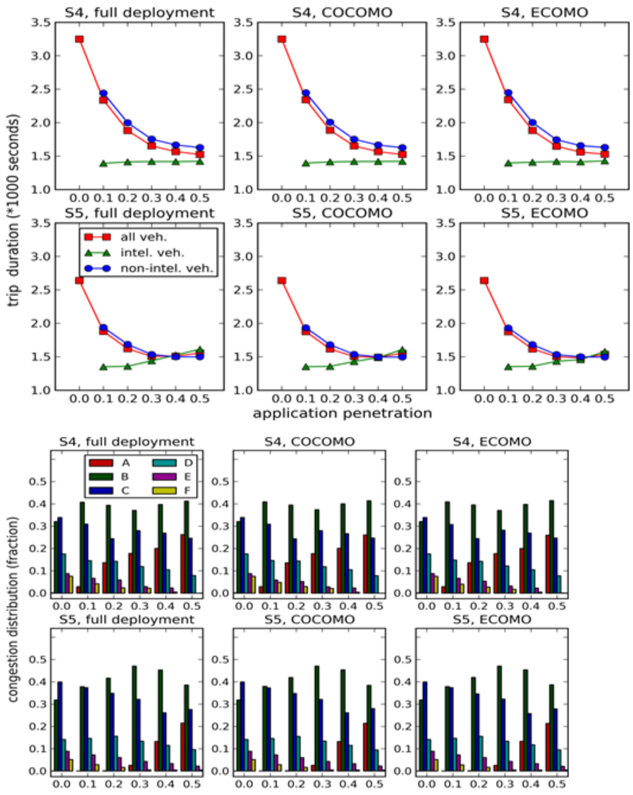
- The master node identifies a set of worker nodes, M map worker nodes and R reduce worker nodes, that execute the map function and the reduce function, respectively. It also defines two hash functions, the one to map a vehicleID to a unique map worker node, and the other to map an edgeID to a unique reduce worker node.

ADVANCEDTRAVELER INFORMATION SYSTEM

In the previous chapters a multi-modal Intelligent Transportation System (ITS) is de- signed that generates edge level traffic information (vehicle flow, congestion, speed) in real time for the whole road network. The two models, namely COngension COverage MOdel (COCOMO) and Edge COverage MOdel (ECOMO) are developed for ITS infras- tructure deployment and edge level speed estimation. The performance of the proposed ITS is evaluated for quality of generated traffic information (error in traffic parameters' estimation) and availability of traffic information (spatio-temporal coverage). Also, the feasibility of large scale deployment of the ITS is established by designing a distributed computing framework and analyzing computation, communication and storage require- ment.
The network wide real time traffic information can be used by traffic applications for a variety of purposes. For example, an Advanced Traveler Information System (ATIS) uses real time traffic information to help the commuters in trip planning. An Advanced Traffic Management System (ATMS) uses traffic information for adaptive traffic light control, enforcing speed limits and lane control, or suggesting diversions to avoid congested regions in a road network. The Advanced Public Transportation System (APTS) uses real time traffic information to estimate the arrival time of public transport buses at different stations and plan trip schedule of buses.

ANALYSIS OF SIMULATION RESULTS

Simulations are carried out to evaluate the effect of application penetration and speed estimation error on the average trip duration and congestion distribution in a road net- work. The metrics are compared for the full deployment model and the proposed models (COCOMO and ECOMO). In the full deployment model, ITS infrastructure and hence accurate speed estimation is available for all the edges in the road network.
Figure a shows the effect of application penetration on average trip duration of intelligent vehicles, non-intelligent vehicles (uninformed commuters), and all the vehicles for full deployment model, COCOMO and ECOMO. Figure b shows the effect of ap- plication penetration on congestion distribution in the road network, for all the scenarios



Effect of Application Penetration

V CONCLUSION

Due to urbanization, the vehicular traffic has increased tremendously in the road net- work. The available road infrastructure is stretched to its capacity, specifically during peak hours. Due to increased traffic congestion, the average time spent on the road by commuters has increased significantly. An Intelligent Transportation System (ITS) gen- erates fine grained vehicular traffic information in real time which can be used to optimize traffic movement in a road network. It has potential to reduce traffic congestion and make the commute more efficient and safer.
However, deployment and maintenance of ITS sensors and related infrastructure on all the edges in a road network is costly. With this

reasoning, a variety of alternative sources have been examined in literature for quality of generated real time traffic information. The cellular network is widely deployed world wide but has large location error (150-500 meters) reported in the literature. When these location traces are used for generating vehicle trajectories, the edge level speed estimation has a mean error of more than 15%. We observe that most of the related work focus on processing of cellular signaling data (to reduce location error) with very little emphasis on designing algorithms for generating traffic information.

The GPS probe data are shown to be a feasible source of traffic information for road networks carrying relatively homogeneous traffic (only four wheelers). However, in developing countries like India, where the traffic is heterogeneous and dominated by majority of GPS-less two wheelers, the GPS probes data alone is not a viable solution for generating real time traffic information.

To generate vehicle trajectories using erroneous location data collected from cellular network, a map matching algorithm was developed. To our surprise, no map matching algorithm was found in the literature that processes location data with such high error presented by cellular network. The map matching algorithm processes a series of location estimates of a vehicle before associating it to an edge. This enables the accurate vehicle trajectory generation but also adds a time lag. The vehicle trajectory is used to compute vehicle flow, space occupancy and congestion estimation. To remove the time lag in the traffic information and to make it real time, the temporal extrapolation using exponential moving average and polynomial regression is attempted. The simulation results show that polynomial regression based extrapolation is more accurate than exponential moving average. In both the cases, the mean estimation accuracy of more than 90% is achieved for all the traffic parameters.

Future Work

A set of realistic simulations is used to evaluate performance of the proposed Intelligent Transportation System (ITS). As a future work and a step towards large scale deployment, a prototype system can be built and evaluated.

It is assumed that all the vehicles are equipped with a cell phone and are tracked using cellular infrastructure. As a future work, we aim to evaluate the signaling overhead incurred in cellular network for tracking all the vehicles. The effect of tracking only a fraction of the vehicles (to reduce signaling overhead) on accuracy of edge level traffic estimation needs to be analyzed. Detecting presence of traffic lights at junctions by processing historical data of GPS probes can be attempted.

In the proposed ITS, deployment of static (non-moving) ITS infrastructure is assumed. Recently the interest has been developed in using mobile sensors and certain combina- tions of static and mobile sensors for traffic monitoring. The proposed infrastructure deployment models can be extended to consider these new developments.

REFERENCES

- "India transport report (volume 1)- moving India to 2032," National Transport De- velopment Policy Committee and Planning Commission, Government of India, 2014.
- "Road transport year book 2009-10 and 2010-11," Transportation Research Wing, Ministry of Road Transport and Highways, Government of India, July 2012.
- "India transport report (volume 2)- trends in growth and development of transport," National Transport Development Policy Committee and Planning Commission, Gov- ernment of India, 2014.
- D. Schrank, T. Lomax, and B. Eisele, "Urban mobility report," Texas Transportation Institute, September 2011.
- Code of Federal Regulations(CFR), Chapter 23, Section 940, 2001.
- J. S. Sussman, "Perspectives on Intelligent Transportation Systems (ITS)," Springer, 2005.
- "Intelligent transportation systems benefits, costs, and lessons learned," Publication Number: FHWA-JPO-14-159, U.S. Department of Transportation, June 2014.
- "Press release no. 65/2015," Telecom Regulatory Authority of India, September 2015