Internet Control Plane Event Identification using Model Based Change Point Detection Techniques

S.P. Meenakshi
Department of Computer Science and Engineering
IIT Madras, India

S.V. Raghavan
Department of Computer Science and Engineering
IIT Madras, India

Abstract

In the raise of many global organizations deploying their data centers and content services in India, the prefix reachability performance study from global destinations garners our attention. The events such as link/node failures and DDoS attacks occurring in the Internet topology have impact on Autonomous System (AS) paths announced in the control plane and reachability of prefixes from spatially distributed ASes. As a consequence the customer reachability to the services in terms of increased latency and outages for a short or long time are occurring. The challenge in control plane event detection is when the data plane traffic is able to reach the intended destinations correctly. However detection of such events are crucial for the operations of content and data center industries. To capture the events we need extreme monitoring infrastructure. By monitoring the spatially distributed routing table features like AS path length distributions, spatial prefix reachability distribution and covering to overlap route ratio, we can detect the control plane events. In our work, we study prefix AS paths from the publicly available route-view data and analyze the global reachability as well as reachability to Indian AS topology. The temporal pattern analysis on distributed peer prefix announcements are performed to understand the occurrence of Internet wide events. To capture the spatial events in a single temporal pattern, we propose a counting based measure using prefixes announced by $x$% of spatial peers. We measure and characterize prefix reachability by using this measure. Employing statistical characteristics change point detection and temporal aberration algorithm on the time series of the proposed measure, we identify the occurrence of long and stochastic control plane events. The impact and duration of the events are also quantified. We validate the mechanisms over the proposed measure using the SEA-Me-We4 cable cut event manifestations in the control plane of Indian AS topology. The cable cut events occurred on 6th June 2012 (long term event) and 17th April 2012 (stochastic event) are considered. Other evidences like upstream changes of major transit and originating ASes of Indian AS topology and peering changes in the route-view table are correlated to confirm the occurrence of the control plane events.

Keywords: Control Plane Events, ARIMA Models, Change Point Detection, Spatio Temporal Analysis, Temporal Aberration

1 Introduction

In the raise of many global organizations deploying their data centers and content services in India, the prefix reachability performance study from global destinations garners our attention. Particularly online services provided from Indian companies to its European and US clients heavily rely on the Internet. The outages due to cable cuts and its impact on bandwidth and delay to the Indian industries are reported in news reports [BBCNews, 2012, GoogleNews, 2008, TimesOfMalta, 2008]. The events such as link/node failures and DDoS attacks occurring in the Internet topology have impact on Autonomous System (AS) paths and reachability of prefixes from spatially distributed ASes. As a consequence the customer reachability to the services in terms
of increased latency and outages for a short or long time are occurring. The events occurring in the control plane can be classified as stochastic and long term events. Stochastic events are defined as the events that have performance impact of one day. Long term events are defined as the events that have performance impact that prolongs more than a day. The performance impact can be quantified using prefix reachability count and the duration.

When the data plane traffic is not able to reach the intended destinations, the outages are perceived immediately and reported in the blogs and news reports. In case of the data plane traffic is being able to reach intended destinations correctly with degraded performance then the events happening in the control plane are not getting much attention. But identifying these events are crucial for the operations of content, data and call center industries. The Sea-Me-We4 submarine cable that interconnects India to Europe and Middle East got cut between Malaysia and Thailand on June 2012 [BBCNews., 2012]. But the traffic is rerouted via other routes with increased latency. To capture such events we need a distributed monitoring infrastructure. By monitoring the features like AS path length distributions, spatial prefix reachability distributions and covering to overlap route ratio we can detect the control plane events.

The publicly available route-view data provides [Routeviews., 2003] the control plane data collected from its geographically distributed peers. Using this data we can characterize the required features for the problem under consideration. We have analyzed the temporal prefix reachability patterns from spatially located peers with respect to Indian AS topology. Based on the observations, we propose a measure that captures the Internet wide control plane activities in a single temporal pattern. The measure counts the reachable prefixes to a country level AS topology from spatially distributed locations. Here the locations are inferred from the locations of peers. The temporal pattern constructed using the measure is analyzed for time series modeling.

In our work, time series model is used to capture the long and short term prefix announcement deviant behaviors that are manifestations of events. ARIMA models are used for generating the time series with different characteristics. To make the non stationary time series compliant for ARIMA modeling, mean change point detection technique is used to identify stationary segments in the time series. Temporal aberration algorithm is used on ARIMA forecasting to capture the stochastic events. Long term events are identified using the change point detection technique. We validate the mechanisms applied on the proposed measure using the SEA-Me-We4 cable cut events that have performance impact on Indian AS topology.

The paper is organized as follows. BGP anomalous behavior study carried out in the literature for different large scale events are discussed in section 2. Route-view data and country level analysis for Indian AS topology are discussed in section 3. Section 4 deals with measure selection criteria. The model based event identification mechanisms are presented in section 5. The mechanisms validation is done in section 6 followed by conclusion in section 7.
2 Related Work

In literature on BGP deviant behavior analysis, the measure widely used to identify the abnormal behavior is announce and withdraw reachability information available in BGP updates. The studies on BGP instabilities and dynamics [Labovitz et al., 1998; Li et al., 2007] consider 10 distinct BGP attributes from update messages to summarize every minute BGP activity. The current and a decade ago BGP dynamics are compared using the BGP attributes in the study. It is found that the forwarding dynamics are dominant and also consistent across different days. The BGP activities exhibit major changes in the number of announced or withdrawn prefixes from the ASes due to the occurrence of unusual events. The events such as prefix interception attack [Zhang and Pourzandi, 2012], prefix hijacking attacks [Zheng et al., 2007], political censorships [pol, 2011a,b], hurricanes, and cable cuts [Li and Brooks, 2011] are studied using BGP data as the primary data source. The BGP update attributes are used in [Li and Brooks, 2011] to measure the impact of Internet earthquakes by analyzing the deviant behavior of the attributes. The BGP routes from the updates to the respective countries [pol, 2011a,b] and Youtube query traffic are measured to identify the Internet blackouts. The routing paths to geographically distributed web servers are [Xu et al., 2011] used to understand the AS and router level firewall infrastructure for keyword based filtering. Average prefix path length and trace route latency measurements are used to identify the detoured Facebook traffic via China telecom [Zhang and Pourzandi, 2012]. The root cause of the event is identified as reduced prepended AS path announcement to Facebook prefixes. Prefix hijacking detection approaches use inconsistencies in route advertisements, route qualities and hop count monitoring from deployed vantage points. In our work, we use time series of prefix reachability count to a country level AS topology announced by x% spatially distributed peers to identify the events. The measure is used to quantify the reachability impact and duration of long and short term events.

The events are captured based on the deviant behavior from the normal activity. Different mechanisms are used to identify the abnormal behavior. The work on I-seismograph [Li and Brooks, 2011] uses various BGP attributes to identify the deviant behavior. The K-Medoids clustering algorithm is used to cluster the attributes into normal and abnormal states. The impact of a single data bin is computed with respect to the normal cluster. The impact during the monitoring period is computed based on how all the data bins collectively deviate from the normal cluster. In our work, we use mean change point detection algorithm on time series of prefix reachability count announced by spatially distributed peers, for detecting long term events. A mean change in the segment using identified threshold i.e., greater than 15% of total prefix count, is considered as a significant long term event. Temporal aberration algorithm is used to detect stochastic events. The impact of both the events are quantified using the prefix reachability count with respect to a moving average. The time series modeling of the measure has an advantage that it can be correlated with other time series measures such as major link events and attacks to infer the root cause for the occurrence of the events.
### Table 1: Peer Spatial Location Distribution

| Asia | Europe | North America | Australia | Africa |
|------|--------|---------------|-----------|--------|
| 2    | 10     | 23            | 1         | 2      |

### 3 Route-view Data and Country Level Analysis

Route-view snapshot carries route information collected from a maximum of 38 peers located in different places. The BGP feeds collected with an interval of two hours are archived as time stamped snapshots in [Routeviews, 2003]. The mandatory BGP route attributes are prefixes, next-hop and AS path. The prefixes are entered in ascending order of their numerical values along with other attributes. The next-hop attribute of the BGP route provides the information on advertising ASes IP address. In route entries of the snapshot, the next-hop indicates the IP address of the peer. Two different next-hop address to an AS peer can be interpreted as the BGP feeds are collected from two BGP border routers of the same AS. The AS path entries for each prefix is a sequence of ASes starting with the peer AS, followed by intermediate ASes in the path and end with the AS that originates the prefix. The AS paths announced for a prefix by different peers are entered consecutively in the snapshot. Hence counting a prefix consecutively until a change in prefix occurs provides the information from how many peers a prefix can be reachable at that time. We have extracted and grouped the geographically located peers from the snapshot based on continents. This exercise is to understand the number of representative peers in each continent. The distributions of the peer locations in five continents are given in the table 1. The continents Asia, Australia and Africa have less than 10 percentage of total peers. South America has no peer representation at all.

We have considered daily snapshots that are time stamped to 0000 hours from 01-01-2012 to 31-12-2012 in our work. Using APNIC [APNIC, 1992] Regional Internet Registry (RIR), we extracted allocated Indian AS numbers. The APNIC RIR contains the static record of AS numbers, allocated IPv4 and IPv6 prefixes for countries in Asia Pacific Region. The extracted Indian AS numbers are used to filter the routes for Indian ASes from the daily snapshots. The prefix counts announced globally and to Indian ASes by different peers are given in table 2. Hereafter we refer the path announcements to all the prefixes in complete snapshot as global. We have observed in the route-view snapshots that peers with an average of one, dropped or included with varying time intervals. For instance, the peer AS located in Romania: AS 39756 ceased the peering from 27-01-2012 to 28-08-2012 and resumed on 29-08-2012. The peer AS 3741 located in South Africa started the peering only from 22-07-2012. Peers temporal dynamics with respect to global and Indian AS topology is given in figure 1. From the figure 1 we can see that there is an occasional peer count drop of one to Indian AS topology but not in the global level. After analyzing the extracted data, the peer involved in such drop is identified as AS 2905.
Table 2: Announced Prefix Counts: Global and India

| Date       | Type  | Peer Count | Peers                                                                 | Prefix Counts            |
|------------|-------|------------|----------------------------------------------------------------------|--------------------------|
| 01-01-2012 | Global| 37         | 286 293 701 812 852 852 1221                                         | 380992 384469 379432 373237|
|            |       |            | 1239 1299 1668 2152 2497 2905                                         | 381070 381067 381843 379792|
|            |       |            | 2914 3130 3130 3257 3303 3356                                         | 376669 379936 382751 381453|
|            |       |            | 3549 3549 3561 5056 5413 6539                                         | 2474 380729 381143 381135|
|            |       |            | 6762 6939 7018 7660 8001 8492                                         | 380480 150422 378602 380738|
|            |       |            | 11537 11686 13030 22388 31500                                         | 378630 379754 381341 380096|
|            |       |            | 39756                                                                | 379826 381433 382521 379882|
|            | India | 37         | 286 293 701 812 852 852 1221                                         | 17135 17160 17136 17139 17132|
|            |       |            | 1239 1299 1668 2152 2497 2905                                         | 17132 17150 17133 14915 17135|
|            |       |            | 2914 3130 3130 3257 3303 3356                                         | 17141 17153 1 17134 17150 17150|
|            |       |            | 3549 3549 3561 5056 5413 6539                                         | 17148 4677 17132 15565 17134|
|            |       |            | 6762 6939 7018 7660 8001 8492                                         | 17133 17103 17115 17116 17134|
|            |       |            | 11537 11686 13030 22388 31500                                         | 17134 17134 17178 15256 17158|
|            |       |            | 39756                                                                | 289 17159 17149 289 17472 17148|

Figure 1: Peers Temporal Dynamics
located in South Africa. It announces only one prefix that belongs to Google corporate network AS 45566 and occasionally drops announcing the prefix.

Next, we have analyzed the temporal prefix announcement patterns extracted from each of the 38 peers for India and compared it with the global level patterns. In the normalized scale, 25 of the global level temporal patterns exhibit a linear trend with only one significant drop event that has occurred on 17th April 2012. For normalization, we use a scale down factor computed as difference between maximum and minimum temporal values. The extracted prefix announcement patterns to India significantly varies in 18 out of 38 peers by exhibiting different raise and drop events. The rest of the 20 peers prefix announcements have similar temporal patterns with three visibly significant events. First one is a long term drop event from 15th March to 5th April. Second one is a stochastic drop event in prefix announcement that appears on 17th April. Third one is long term raise event that appears from 7th July to 29th July. The second and third events co-inside with the time of cable cut occurred in SEA-Me-We4 submarine cable. For the purpose of further analysis, we group the peers into two groups based on the aforesaid observations. Peer ASes with similar temporal prefix announcement patterns (20 peers) are placed in group I. Group II is placed with peers having different prefix announcement patterns (18 peers). The peer ASes and their locations in Group I and Group II are given in table 3.

The representative temporal prefix announcement patterns for global category, Group I and Group II categories for India are given in figure 2. The varying temporal patterns from different peers invoke the intuition that the stochastic and long term prefix drop/raise events occur network wide with different magnitudes (prefix counts) due to various causes. At a time point, the events are manifested in one or multiple peer temporal patterns. But in a countrywide view, we are interested to find answers for the following questions. How many prefixes are reachable from maximum number of peer locations? How the prefix announcements from maximum number of peers vary temporally? These two questions will answer the impact on prefix reachability from different locations and the duration of the event. To address these two questions we are proposing a spatio temporal prefix counting measure.
4 Measure Selection Criteria

Spatio temporal measures provide good indication for control plane events that take place spatially in the Internet. The measures are combination of two components namely long term trend and irregular variations. Long term trend is induced by raise in number of new content and data center service networks. The irregular variations are due to node/link failures, popular events and DDoS attacks. We are interested to identify the irregular variations and find out the specific times the impact of the events is higher or lower. The prefix count reachability from different peer locations is the considered feature measure in our work. The spatial locations are interpreted from the spatially located peers associated with BGP feeds to the route-view servers. Noticeable deviations in the number of prefixes reachable from x % of spatially distributed peers often indicate undesirable control plane events. The value for x is chosen based on the number of maximum prefix announcement peers for a country level. The rationality behind choosing the percentage of peers and the value for it is discussed in section 4.1.

Our general approach to the control plane event detection problem is to first establish a measure that reflects the global Internet operating conditions (prefix count reachable from x % of spatially distributed peers) whose expected behavior we can discern from individual peer temporal pattern analysis and then determine the duration and impact of the deviant behavior. Two techniques are employed on the measure for the purpose of identifying long and short term prefix based events. By considering statistical characteristics change in the long term events, mean change point detection technique is used to detect and quantify that kind of events. ARIMA models are used in short term event detection and quantification. Changing network conditions and continuously evolving prefix patterns induce highly fluctuating behavior on prefix reachability measures over time. It is reasonable to
assume that for a limited span of time we can model irregular behavior patterns using time series models such as ARIMA. This model is used to detect one step ahead deviant behavior which is as an indication of stochastic control plane events.

4.1 The Measure and Empirical Measurement

In the routing table data, we have reachability information for unique prefixes from each of the peers. There are \( X_t \) peers, where \( x_1, x_2 \ldots x_n \) are spatially distributed peers at time \( t \). \( N_t \) is maximum number of peers announcing prefixes at time \( t \). \( Y_t \) is vector of prefixes \( y_1, y_2 \ldots y_n \), announced by \( X_t \). The maximum unique prefix value \( y_{\text{max}} \) is computed as \( y_1 \cup y_2 \ldots \cup y_n \). Since the prefix values are evolving in nature and subjected to irregular variations, we take average of 7 prior and current values for our analysis at time \( t \). Each of the prefix is announced by \( X \) peers which varies between \( 1 \ldots N_t \) at time \( t \). We create different percentage of peer bin ranges and counted the number of prefixes announced by each peer bin range. The counting measure is interpreted as number prefixes announced by the percentage of peers at time \( t \). Each bin measurement is compared with \( y_{\text{max}} \) to find out the relative rank at time \( t \). When \( n \) peers increase announcing \( y \) prefixes each at time \( t \), then the prefix count of one or more peer bin ranges will increase. Similarly prefix count drop will occur in one or more peer bin ranges when \( n \) peers drop \( y \) prefixes each. The temporal variations in the relative rank of the peer bins is an indication of events. This change will also be manifested in the temporal patterns of each of the peer bin range. We are interested to identify a peer bin range that announces greater than 95 % of the prefixes. Since \( y_i \) values are not equal and have variations, we want to find out the peer bin range that announces at least 95 % of \( y_{\text{max}} \). Initially the peer bins are assigned with the following percentage ranges.

1. >90 %
2. 81 to 90 %
3. 51 to 80 %
4. 28 to 50 %
5. 14 to 27 %
6. 6 to 13 %
7. < 5 %

The initially assigned bin values can be modified according to the empirical data under consideration. This procedure is to identify the appropriate bin percentage range that announces at least 95 % of prefixes. The prefix announced in this bin range is considered temporally to identify the events and the impacts.
We have measured the spatio temporal prefix count measure on AS path data to Indian prefixes that are extracted from daily route-view snapshots. Further more, time series modeling is employed on the measure for event detection. Each peer feed has unique path entry for a prefix in the route-view table. The number of paths are equal to number of reachable unique prefixes. We hold this assumption since multihoming contributes to less than 3% of the paths. The number of paths announced to each prefix are counted and added to the corresponding peer bin range. The initial range of peer bin percentage and the prefix count reachable from each range for Indian AS topology is given in Table 4.

Table 4: Prefix Reachability From Range of Spatial Locations

| Date       | Unique Prefixes | > 90 % | 81-90 % | 51-80 % | 28-50 % | 14-27% | 6-13 % | < 5 % |
|------------|----------------|--------|---------|---------|---------|--------|--------|-------|
| 01-01-2012 | 17502          | 13286  | 3813    | 33      | 13      | 47     | 23     | 287   |
| 01-02-2012 | 17225          | 13256  | 3847    | 16      | 14      | 46     | 28     | 18    |
| 01-03-2012 | 17215          | 13350  | 3744    | 30      | 10      | 46     | 22     | 13    |
| 12-29-2012 | 19294          | 11456  | 7701    | 34      | 16      | 38     | 35     | 14    |
| 12-30-2012 | 19292          | 11428  | 7730    | 34      | 14      | 37     | 35     | 14    |
| 12-31-2012 | 19222          | 11499  | 7592    | 40      | 8       | 36     | 33     | 14    |

From the extracted sample data for the duration of 01-01-2012 to 31-12-2012 given in the table, we find that the prefixes grouped under first and second range is approximately 99% of the unique prefixes. It can be interpreted as 77% of the unique prefixes are announced by greater than 90% of the peers in different locations. In addition, another 22% of the unique prefixes are announced by 80-90% range of the peers. Cumulatively 99% of the prefixes are announced by more than 80% of the peers. In the observation duration, maximum temporal dynamics occurred only in these two ranges. When there is a drop/increase in above 90% range, most of the time the equal value of increase/drop is observed in 80-90% range. From this, we can safely infer that less than 10% of peers are only involved in temporal dynamics most of the time. From the extracted data, we found that route-view routers involved in peering with approximately 38 ASes. In few of the ASes at most two routers are involved in peering activity.

Considering the temporal peer dynamics from the aforesaid two ranges, we are interested to identify the maximum percentage of peers announcing greater than 95% of unique prefixes initially. So we computed the prefixes announced by each percentage of peers above 80% at time t. The announced prefix count versus percentage of peers announcing the prefixes are given in figure 3. When there is an event in the control plane, then it is imperative that the prefix count announced by this spatially located peers will have impact. We have found that greater than 88% of peers announce more than 95% of the prefixes. This peer percentage is more sensitive to control plane events than the above 90% peers. Two long time (more than a day) drops and five short time drops (one day) that have impact on more than 10% prefixes are observed from the figure 3. Two long time raise events with 1-2% increase in prefix count also seen. We compare both greater than 88 and 90
% peer temporal patterns with the temporal patterns of individual peers given in figure 2. It has been observed that the prefix (drop/raise) events occurred in individual peer patterns are captured in the patterns of both the peer percentages. But based on visual interpretation, above 88% peer prefix announcements captures more events. Hence we take this spatially distributed peer percentage announced temporal prefix counts measure for identification of control plane events. The optimal peer percentage that captures all/maximum events needs further investigation.

5 Event Identification

Events that are happening unusually in the time series data are identified using its deviant behavior from time series model forecasts. For deviant behavior analysis on time series data, it is necessary that the series should meet a set of ideal conditions, such as the data being consistent and trend free. Consistency implies that all the collected data belong to the same statistical population (i.e., a generation process with the same parameter generates all the data). Trend free implies that the time series should be stationary. The time series data can be described using the data generating process and the moments such as mean, variance and autocorrelation of order k. Stationarity is an essential property of time series process. A time series process is said to be covariance-stationary or weakly stationary if its first and second moments are time invariant. A stationary process also has mean reverting property. If the time series holds these properties then only the process model will forecast with good point forecast and 95% confidence prediction interval. The accurate forecasting is essential to capture the
Mean Change Point Detection in Prefix Announcements

![Graph showing changes in prefix count over time with identified change points.](image)

**Figure 4: Mean Change Point Detection on Prefix Count**

deviant behaviors in our case.

But our time series data is non stationary. We can observe two long duration of drops in our 88 % peer bin prefix announcement measure. This indicates parameter change in the generation process. In our measure, non stationarity is present due to factors such as new services, node/link failures and attacks. The prefix announcement evolve temporally with a long term trend due to new services. Factors such as node/link failures and attacks have long and stochastic variations on prefix announcements. The statistical characteristics of the series such as mean changes during long term events. Due to which the time series must be generated using the model with different parameter. Hence to obtain the consistency property for the time series model, we detect the significant mean changes using change point detection technique. Then each mean invariant segment is modeled using ARIMA models for forecasting and through which stochastic deviant behavior events are captured.

The mean variant characteristics on the identified measure during long term events is used in change point detection technique for detecting long term events. Since the spatio temporal measure is dynamic that is subjected to many external factors, long time prefix announcement changes are reasonable to be expected. Hence mean change point detection can be used to find the significant long duration prefix announcement changes.

Stochastic events are identified using temporal aberration algorithm that uses time series methods. We use the mean invariant segments identified by the change point detection technique to fit for ARIMA models. The model parameter values for each segment is identified using ACF and PACF coefficients of that segment. Then using threshold value based mechanism on each segment, significant stochastic changes are identified.
Table 5: Mean Change Points and Prefix Reachability Events

| Time Period     | Segment mean | > 88 % Peer mean | Diff Prefix % | Long Term Event | Stochastic Events | Peak Impact % |
|-----------------|--------------|------------------|---------------|-----------------|-------------------|---------------|
| 01/01 - 05/02   | 17407        | 16867            | 97            | No              | 0                 | 0             |
| 10/02 - 03/03   | 17699        | 13983            | 79            | Yes             | 0                 | 0             |
| 04/03 - 21/03   | 17645        | 12597            | 71            | Yes             | 0                 | 0             |
| 22/03 - 04/05   | 17648        | 13932            | 75            | Yes             | 1                 | 56            |
| 05/05 - 06/06   | 17864        | 17425            | 97            | No              | 1                 | 74            |
| 07/06 - 21/07   | 18136        | 10333            | 56            | Yes             | 1                 | 44            |
| 22/06 - 23/09   | 18374        | 17571            | 95            | No              | 2                 | 59.63         |
| 24/09 - 31/12   | 18972        | 18540            | 97            | No              | 1                 | 58            |

5.1 Change Point Detection

The Change Point Detection is a clustering mechanism on non stationary time series. It is the name given to the problem of estimating the point at which the statistical properties of a sequence of observation change. In this, a cluster is assumed to have same mean value. The clusters are identified using Segmentation Neighborhood (SegNeigh) [Auger and Lawrence, 1989] algorithm based on mean change with respect to global mean. The maximum number of segments needs to be specified for the algorithm. The Cumulative Sum (CUSUM) is computed on the time series data over which SegNeigh algorithm is applied to detect the mean changed segments. The segments that have mean prefix reachability count varying more than 15 % is considered as significant long term event. This threshold value is subjected to the requirement of the Internet Service Providers (ISPs). The change point package [Killick and Eckley, 2011] in R statistical software is used to detect change points. The long and short duration segments are identified with their peak impact values and given in table 5.

5.2 Temporal Aberration Algorithm

The temporal aberrancy detection algorithm is described as algorithm that sequentially evaluate the departure of the observed rate of a measure from what would be expected based on previous history. These algorithms are in general classified based on the underlying methods such as control charts, regression models, time-series methods and scan statistics [Buckeridge et al, 2008]. Considering our non stationary time series measure, we use ARIMA model based algorithm.

The algorithm computes the difference between the baseline measure and the current observation. An event is identified when the difference is greater than a positive threshold or lesser than a negative threshold. The threshold values are taken from the 95 % confidence level prediction intervals of the considered model. ARIMA models have three components namely Auto Regression (AR), Moving Average (MV) and Trend. This model takes care of the temporal evolution of the prefix announcements.
By analyzing Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) coefficients of each segment, the parameter values for AR, MV and Trend components are identified. The ACF and PACF plots for first three segments are given in figures 5 and 6. The lag value that has significant ACF coefficients are assigned for MV parameter of the segment model. For example, segment 1 has significant ACF coefficient up to lag 4 and hence MV(4) is considered. Similarly the lag value that has significant PACF coefficients are assigned to AR parameter of the segment model. In our case none of the segments have significant PACF coefficients and hence AR(0) is assigned for all the segment models. The trend is linear and hence the additive trend is considered in the model. The MV parameter provides the indication on how many past values are taken to compute the base line. The model forecasts one step ahead and provides prediction intervals used as thresholds.

For brevity, we provide model selection and forecasting for segment 4 which spans from time unit 70 to 108 in the time series. The ACF coefficient of this segment is nonsignificant in all the lags except 0. Similarly PACF coefficient is also nonsignificant in all the lags. So we use a special case of ARIMA (random walk model) which is represented by ARIMA(0,1,0). We fit the data to ARIMA(0,1,0) from the time unit 70 to 91 and show the five step ahead forecast for time units 92 to 96 for illustration. The segment data in time unit 92 is stochastic drop event since it deviates significantly from 95 % prediction interval. The model forecasting and prediction intervals are given in figure 7. The point forecasting and prediction intervals for 80 and 95 % confidence levels are given in table 6.

From the figure 7 and the table 6 it can be inferred that one step ahead forecast can clearly capture the deviant behaviors. Except the data point at 92, the data spans from 93 to 96 are well within the 95 % prediction intervals.
Figure 6: PACF for Announced Prefix Counts of Different Segments

Figure 7: ARIMA Model Forecasting with Prediction Intervals
Table 6: ARIMA(0,1,0) Point Forecasting and Prediction Intervals

| Time (days) | Actual | Point | 80 % Low | 80 % High | 95 % Low | 95 % High |
|-------------|--------|-------|----------|-----------|----------|-----------|
| 92          | 9925   | 14202 | 14114.64 | 14289.36  | 14068.39 | 14335.61  |
| 93          | 14229  | 14202 | 14078.45 | 14325.55  | 14013.04 | 14390.96  |
| 94          | 14248  | 14202 | 14050.68 | 14353.32  | 13970.58 | 14433.42  |
| 95          | 14163  | 14202 | 14027.27 | 14376.73  | 13934.78 | 14469.22  |
| 96          | 14160  | 14202 | 14006.65 | 14397.35  | 13903.23 | 14500.77  |

The forecast package [Hyndman and Khandakar, 2008, Killick and Eckley, 2011] in R statistical software is used to do one step ahead forecast for the ARIMA model. By iteratively calling the forecast function of the model, stochastic events are identified and quantified. The identified short term events and their impact are given in table 5.

6 Validation

Using the change point detection technique, we have identified 4 long term events. Legitimate route change events due to link status change usually affect large number of prefixes [Zheng et al, 2007] while route changes due to prefix hijacking usually target specific network prefixes. In our case, each of the detected events has more than 15 % prefix reachability reduction and prevails for more than 10 days. Hence the events should be related with link status change induced by cable cuts. The time period associated with the fourth event (segment 6) is correlated with SEA-Me-We4 cable cut and restoration duration from 07/06/2012 to 21/07/2012 [SMW, 2012]. The total prefix paths to Indian ASes computed from route-view table also indicates a significant path reduction during this period. The stochastic event identified in segment 4 is matching with the same cable cut event occurred on 17/04/2012 that got restored within a day.

We have computed the average number of prefixes announced to Indian AS topology by dividing the total prefix paths using average number of peers. The uniquely filtered prefixes, average number of prefixes and prefixes announced by > 88 % of peers are given in figure 8. All the three measures have the indication for the cable cut events, but with different levels of noise. The route change events can also be observable in the Upstream Betweenness Centrality (UBC) change to an AS under consideration. Here betweenness centrality is computed as number of paths passing through an upstream to the prefixes of particular AS. In the cable cut event, it is reported that the Indian transit AS 9498 has severe impact on its prefix reachability. Hence we computed and analyzed the UBC measure for AS 9498 from the extracted AS paths of Indian AS topology. A maximum of 25 upstreams (some of them may be peers) are found through which the prefixes of the AS can be reachable from global locations. The first 4 upstreams based on the decreasing order of the UBC value is given in table 15.
In this $UBC_i$ represents the paths passing through $i_{th}$ upstream. On 17th April 2012 there is a decrease in the UBC measure for all the upstreams with approximate path drop of 3500. No change in upstream count and the ordering of the upstream is observed. But on 7-06-2012 we observed a change in the upstream order which is based on the UBC value and also a peer drop. In the top three upstreams, there is a path increase to the magnitude of 2500 and in middle few upstreams there is a path drop to the magnitude of 1000. The dropped peer UBC is approximately 5500. Over all there is a path drop of around 4000 is observed to AS 9498. Further more, path drops fluctuating around this value is found upto 21-7-2012. There may be other factors involved in change of paths during this period, but the upstream order change and peer drop evidences show that the cable cut has significant impact on the reachability of the prefixes during this period.
7 Conclusion

In this work, we have analyzed the route-view data for distribution of peer locations from which BGP feeds are collected to the route-view table. The prefix announcements from different spatially located peers are interpreted as reachability of prefixes from those locations. The peer distribution analysis on different continents reveals that the number of representative peers in Asia, Australia and Africa is less than 10 % of the total peers involved in route collection. Hence to understand the events occurring in these regions, we require BGP feeds from more representative peers in the regions. Prefix announcements for Indian AS topology is extracted from the daily route-view snapshots for a duration of 1 year. The temporal prefix reachability patterns to Indian ASes from each of the peers are analyzed. The temporal patterns for 20 peers out of 38 are found to be similar with respect to direction and magnitude of the events. The patterns from other 18 peers exhibit different number of prefix raise and drop events. To capture the events occur spatially in a single temporal pattern and quantify the impact and duration, we proposed a counting based spatio temporal measure on prefix reachability from x % of peers. Using this measure we detect long term events by employing change point detection technique and quantify the impact of each event. The stochastic events are captured using temporal aberration detection algorithm that use ARIMA models on the segment under consideration. The sensitivity and specificity of the mechanisms are validated using the Sea-Me-We4 cable cut events reported in the news blogs. Our future work is to identify the root causes for the other events that induced the aberration in the measure and verify the performance of the mechanisms over the measure with respect to India as well as other countries in the APNIC region.

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