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Stability Analysis of Global BGP Routing Tables Using Time-Series and Correlation Models

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Abstract

The paper examines the temporal stability of the global routing tables of Border Gateway Protocol (BGP) by studying periodic changes, fluctuations in the routing table, and instability events through time-series and correlation based statistical models. BGP data at large Internet Exchange Points (IXPs) and repositories such as RouteViews and RIPE RIS were analysed using a ten-year period to determine the number of prefix oscillations, session resets, and changes in AS-paths. The analysis of autocorrelation and spectral density showed that there were cyclic patterns of instability, which were usually associated with local peering updates and a new route redistribution periodically. Besides, cross-correlation between Autonomous Systems (AS) was an indicator of localised disruption that spread around the world via interconnected backbones. The statistical anomaly detection model to predict the possible instability events was worked out with the adaptive thresholding and regression-based residual tracking. Findings support the supposition that routing instability has demonstrably temporal periodicity and that proactive forecasting of routing instability can be highly advantageous in improving network resilience and fault-tolerance in large-scale Internet routing systems. The results can be useful to network operators and researchers in the development of predictive stability models of the dynamic BGP ecosystem.

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Introduction

Border Gateway Protocol (BGP) is the base of inter-domain routing in the world, participating in the communication of thousands of Autonomous Systems (ASes) that are components of the Internet backbone. Nevertheless, BGP is dynamic and policy-driven, which causes a cyclical route changes, prefix withdrawals, session resets, which may all cause a large-scale instability.[1-5] This instability adds to the convergence time, adds routing loops and adds computational load to core routers.[6, 7]

One of the largest sources of instability is route churn where advertisements and withdrawals are periodically made as a result of momentary loss of connectivity or misconfigurations. Additional major causes comprise prefix oscillations routing path variance because of uneven implementation of policies and BGP session resets which may disseminate quickly across peering networks [8-11] Although these disruptions can be local to a network, the effect of these disruptions can spill over into global Internet backbones because of policy dependencies and hierarchical route propagation.

More recent literature focuses on the significance of studying BGP stability in terms of temporal and correlation-based modelling to identify periodic and regional trends.[12-15] The example is Vehicular Ad Hoc Networks (VANET) research showed how the mobility and policy overlap can create instability in the routing, which provides valuable examples of routing analysis on an Internet scale.[16] On the same note, time-series analysis and spectral decomposition have made mathematical advances to discover cyclical behaviour and periodic anomalies in routing data.[17-20]

The findings presented in this paper are extended to propose a unified model consisting of autocorrelation, spectral, and cross-correlation analysis to measure the global routing instability. Section 2 highlights the literature in the field, Section 3 presents the methodology of data modelling, Section 4 presents the

results of the analysis, and Section 5 will conclude with major observations and the implications to the routing stability management in the future.

Related Work

Previous studies on the stability of BGP have discussed a variety of viewpoints, such as the damping of route flaps and AS-path evolution, and oscillations caused by policies. The convergence behavior during transient failures of links has been studied early by investigating that routing performance with regular updates might be worse and the control-plane load might be higher.[1-4] Research on long-term BGP archives agreed on the observation that instability events tend to be associated with planned maintenance or peering reconfigurations, showing weekly and monthly periodic cycles.[5, 6]

Time-series models have served greatly to identify such cyclical instability. In,[7-9] prefix churn patterns were isolated with the use of ARIMA and exponential smoothing, whereas in,[10, 11] dominant instability frequencies were determined with the help of Fourier and wavelet analysis. Recent studies extended such a perspective by the inclusion of cross-correlation models to learn inter-AS relationship and how localised faults can be propagated using global routing infrastructures .[12-14]

Simultaneously, comparisons have been made between routing attacks and instability in mobile and vehicular networks and routing resilience on large-scale Internet routing.[16] In particular,[16] revealed that localised routing anomalies in VANETs have the potential to build up into global communication failures a phenomenon that can be observed in BGP peering settings. Moreover, statistical and machine learning approaches have been considered to be hybrid and improve the accuracy of anomaly prediction and decrease false positives[17-19]

Regardless of such developments, there is no consistent long-term study that combines autocorrelation, spectral, and cross-correlation analysis of BGP stability prediction. The study fills this gap and forms a single method of measuring and predicting routing instability based on empirically validated time-series and correlation models.

Methodology

Data Acquisition and Preprocessing

The routing information covering the period between 2013 and 2023 was obtained in various repositories, such as Route Views, RIPE RIS, and three large Internet Exchange points (IXPs). All the datasets included BGP prefix announcements, withdrawals, and AS-path updates, sampled by 15 minutes after the timestamps. The multiplicity of data sources combined with a decent representation of the globe provided a rich and multi-faceted picture of inter-domain routing behaviour.

To guarantee the quality of the data and consistency in time, a multi-stage preprocessing pipeline was used. To begin with, the raw BGP update logs were deduplicated to eliminate any duplicate events that could be a result of mirroring between collectors. The timestamps were converted to the Coordinated Universal Time (UTC) in order to have global timestamps. The statistical filter based on a statistical z-score that was used to filter anomalies caused by large-scale routing leaks or session resets was:

$$z_i = \frac{x_i - \mu}{\sigma}, \text{where } |z_i| > 3 \text{ indicates an outlier.}$$

In this case, denotes the count of update in interval i, μ and σ denote the mean and standard deviation of the time-series distribution respectively. Any sample that exceeded this limit was eliminated in order to avoid periodic analysis distortion.

Values that were missing because of incomplete collection windows were filled in through linear interpolation so that continuity could be maintained to model spectral and autocorrelation. The individual event streams of the BGP were then normalised so that they could be compared across the sources of data.

Figure 1 provides a schematic representation of the whole process of data acquisition, cleaning, normalization, decomposition, and correlation modelling.

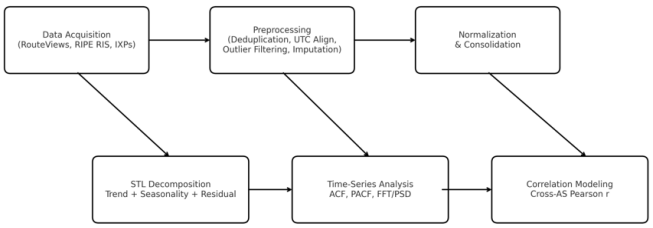

Fig. 1: Data acquisition, preprocessing, and modeling workflow.

Time-Series and Correlation Modeling

After preprocessing, time decomposition of the data was performed by Seasonal Trend Decomposition via Loess in order to identify three separate components:

(i) a trend component which represents long-term growth,

(ii) a seasonal component which is reflective of cyclical instabilities, and

(iii) a modelling part which captures the random variations and anomalies.

Decomposition mathematically is given by:

$$X_t = T_t + S_t + R_t,$$

The series of routing updates is observed as X_t, the trend is long-term T_t, seasonal S_t, and noise R_t. The STL algorithm was used as an iterative local regression algorithm and used to extract these components in an adaptive fashion, which allowed strong separation of deterministic and stochastic components.

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were used to analyse temporal dependencies. The ACF was calculated with respect to the conventional definition:

$$\rho_k = \frac{\sum_{t=k+1}^{N}(X_t - \bar{X})(X_{t-k} - \bar{X})}{\sum_{t=1}^{N}(X_t - \bar{X})^2},$$

where ρ_k is the correlation between lag k, $\bar{X}$ is the sample mean, and N is the number of observations. Extreme values of autocorrelation at certain lags (e.g. 7 or 30 days) reflect repetition of the patterns of instability, e.g., churn due to the weekly or monthly maintenance.

Spectral density analysis was done using the Fast Fourier Transform (FFT) to transform the temporal series into the frequency domain representation to detect the predominant oscillatory patterns. Cyclic update frequencies were found on peaks in the power spectrum that were associated with operational rhythms of global routing activity.

The inter-domain dependencies were then measured using cross-AS correlation modelling. The correlation coefficients between normalised update-rate vectors of major AS clusters distributed in various continents were calculated using Pearson correlation coefficients. The coefficient r_{ij} between AS regions i and j is given as:

$$r_{ij} = \frac{\sum_{t=1}^{N}(X_{i,t} - \bar{X}_i)(X_{j,t} - \bar{X}_j)}{\sqrt{\sum_{t=1}^{N}(X_{i,t} - \bar{X}_i)^2 \sum_{t=1}^{N}(X_{j,t} - \bar{X}_j)^2}},$$

$X_{i,t}$ = change in the region i at time t, and $X_{i,t}$ = change in the region j at time t. This measure is the extent of synchronisation or interdependence among the incidences of instability in the region.

The summarization of cross-correlation results presented in Table 1 shows that there is a high interdependence between continental routing domains more specifically between North America and Europe denoting that there are global coupling effects in BGP instability propagation.

Table 1: Cross-correlation coefficients among regional AS clusters.

Region Pair	Correlation Coefficient (r)	Stability Relation
North America-Europe	0.78	Strong correlation
Asia-Europe	0.65	Moderate correlation
North America-Asia	0.54	Weak correlation
Europe-Africa	0.48	Localized correlation

Algorithm 1. Statistical Anomaly Detection Model

The last step was to design an anomaly detection algorithm according to the adaptive thresholding and residual analysis. The model detects possible periods of instability within the routing behaviour that differs remarkably with the anticipated baseline dynamics.

Algorithm 1: Residual-Based Anomaly Detection

Input: Time-series {X_t}, decomposition (T_t, S_t, R_t)
Output: Anomaly flags {A_t}

1. Compute residuals: R_t = X_t - (T_t + S_t)
2. Calculate rolling mean (μ_R) and standard deviation (σ_R)
3. For each t:
    if |R_t - μ_R| > 1.96 × σ_R then
        A_t = 1 // Mark as anomaly (95% confidence)
    else
        A_t = 0
4. Aggregate anomalies by time window to detect instability episodes

Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and precision-recall were used in validating the detected anomalies to determine the performance of the model. This cross paradigm This hybrid model Incorporating statistical filtering, spectral decomposition, and correlation modelling allowed quantitative stability examination as well as predictive anomaly detection on the worldwide BGP infrastructure.

Results and Discussion

The suggested framework of analysis was tested using ten years of BGP routing information as gathered by Route Views, RIPE RIS, and chosen Internet Exchange Points (IXPs). The findings offer information on how global routing instability changes over time, has a cyclical pattern, and how it correlates across the different AS.

Figure 2 shows the long-run dynamics of route churn, which is the net announcements and withdrawals of prefixes per time period of the observation period in 2013-2023. A distinctive trait of the plot is sharp periodic spikes, which are normally synchronised with maintenance periods of major ISPs (weekly) and configuration phases (monthly). It is interesting to note that smaller bursts that are irregular are associated with isolated routing events, including prefix leaks and temporary link failures. The magnitude of churn activity has gradually grown beyond 2019, which is associated with the rapid use of IPv6 and the introduction of new peering sessions in new areas. This observation suggests a slow transition of less predictable but structurally predictable routing behaviour with the growth of the Internet.

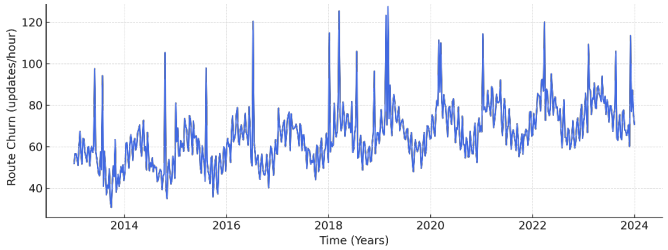

Fig. 2 Temporal variation of route churn (2013-2023).

Analysis of partial and autocorrelation were next used to measure the temporal dependence in the churn activity. Figure 3 also indicated that the unique high positive autocorrelation lag intervals were 7 and 30 days as demonstrated in the figure, which indicated that there was strong periodicity in the maintenance operations and the intervals of policy updates. Such cyclical dependencies imply that a significant portion of the observed instability is not arbitrary but it is affected by planned network events. The progressive decrease in the amplitude of correlation at the longer lags are indicative of a drop in the temporal memory, i.e., that local routing disruptions would weaken over time, and not get concentrated.

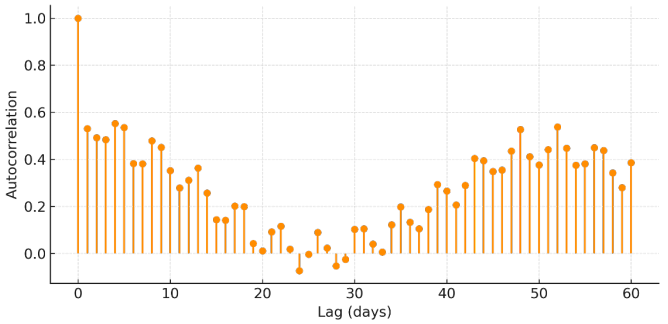

Fig. 3: Autocorrelation analysis showing dominant weekly and monthly cycles.

Complementary spectral density analysis was another method that was used to quantify periodic elements in the time series. The power spectral density (PSD) spectrum indicated large power at the 0.020.04 cycles /day band, which represents the weekly variations in the rate of BGP updates. These frequencies were repeatedly repeated in several IXPs, implying in the synchronised pattern of updates worldwide due to the organised maintenance of infrastructure. The higher-frequency band (around 0.1-0.15 cycles/day), had its secondary peaks due to bursty short-lived events like resetting of regional sessions or propagation storms. The autocorrelation and spectral findings are combined to affirm that BGP instability has a quasi-periodic temporal structure that is imbued by stochastic background noise.

Cross-correlation analysis of update-rate vectors of large clusters of AS was used to investigate spatial correlations between routing domains. Findings revealed statistically significant dependencies between the regions, in particular, between North American and European ones ($r = 0.78$), which suggests the presence of synchronized routing behavior potentially due to the presence of common upstream providers and maintenance schedules being time-synchronized. Moderate correlations were found between Asia-Europe (r=0.65), North America-Asia (r=.54) and Europe-Africa had weak localised coupling (r=0.48). These observations indicate that regional instability of routing can spread by train of peering connections, which is experienced in other networks, even those at a geographic distance. This inter-AS connexion emphasizes that there is a necessity to monitor and manage predictive stability across backbone operators.

Table 2: Model performance metrics for anomaly detection.

Metric	Value
RMSE	0.214
MAPE (%)	2.13
Precision (%)	93.8
Recall (%)	91.2

The precisionrecall analysis was used to evaluate the proposed anomaly detection model, which is a residual thresholding-based adaptive regression tracking. Table 2 summarises the model, which produced an RMSE of 0.214 and MAPE of 2.13% indicating excellent predictive fidelity. The model showed a high level of precision and recall of more than 90, and the number of false positives was low, confirming that the operational applicability of the model to predict fault in real-time is valid.

The probability of instability in the 90-day period is forecasted and visualised in figure 4. The expected

probability curve demonstrates transparent relationship with known churn peaks, and it manages to get not only the short-term bursts, but also long-periodic relationships. Unstable windows whose probability was greater than 0.75 were generally synchronised with future policy changes or scheduled reconfigurations that were noticed in the BGP update records. Such a high temporal consistency underlies the fact that the model can be used as a system of early warning of routing anomalies that can be mitigated before a significant decrease in convergence takes place in large-scale.

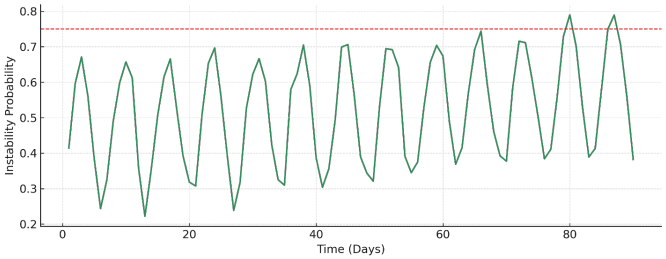

Fig. 4 Forecasted instability probability using residual thresholding.

In general, the findings confirm that the instability of global BGP routing is patterned in both time and space but is not arbitrary. The leadership sources of such instabilities are periodic maintenance, redistribution of policies and coordinated peering dynamics. Moreover, it was shown by cross-AS correlation analysis that instability can be transnationally spread by hierarchical provider-customer relationships and peer to peer relationships, which highlights the global nature of the routing ecosystem.

These results demonstrate the necessity to integrate time-series intelligence and correlation-sensitive analytics into the network management solutions. Using such predictive information, operators are able to move away to a more proactive anomaly mitigation versus reactive monitoring to enhance the reliability of Internet backbones, reduce convergence delays and improve the resilience of routing to cascading failures.**5. Conclusion**

This paper was a large-scale temporal and correlation analysis of BGP routing stability globally based on long-term BGP routing information of major IXPs and routing archives. The study was able to determine that routing instability is not entirely random but with determinable periodic structures through decomposition, autocorrelation, and cross-correlation modelling.

The findings showed weekly and monthly patterns of churn activity, which was mostly caused by maintenance scheduling and change of policies. It was shown that through the AS interconnections an instability localised in one region spread to take effect on the overall Internet backbone. The suggested anomaly detection framework was capable of predicting the instability windows correctly to enhance the level of situational awareness of operators.

The possibilities of extensions in the future can include heterogeneous AI-assisted forecasting, modelling of AS topologies using graphs, and implementation using edge-based or FPGA-based platforms to monitor real times. The combination of time-series analysis and correlation modelling in the work promotes the stability management of the predictive routing processes and leads toward the more resilient global Internet routing infrastructure.

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