Towards a Predictive Internet

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Since the early days of the Internet (Arpanet in 1970), the topic of Routing Protocol Convergence Time (time required to detect and reroute traffic in order to handle a link/node failure) has been a top-of-mind issue. A number of protocols and technologies have been developed and deployed at a large scale with the objective of improving overall network reliability. Although such approaches have dramatically evolved, they all rely on a reactive approach: upon detecting a network failure, the traffic is rerouted onto an alternative path. In contrast, a proactive approach would rely on a different paradigm consisting in rerouting traffic before the occurrence of a predicted failure onto an alternate path that meets application Service Level Agreement (SLA) requirements.

Myth or reality? The notion of prediction refers to the ability to anticipate/forecast a network state (such as a dark/grey failure) that would impact the application experience, but also to determine whether an alternative path that is free of failures exists. This short white paper introduces the emergence of a Predictive Internet using learning technologies along with few results derived from the deployment of such technology at scale.

A new world, with new challenges

Network recovery has been a topic of high interest in the networking community since the early days of the Arpanet in 1970. Nonetheless, the paradigm has not changed much: first, a failure must be detected, followed by traffic rerouting along an alternate path; such a path can be either pre-computed (i.e., protection) or computed on-the-fly (i.e., restoration).

Let's first discuss “Failure detection”. The most efficient approach is to rely on inter-layer signaling whereby lower layer may be able to detect a layer-1 failure (e.g., fiber cut) triggering a signal across layers. Unfortunately, a large proportion of failures impacting a link or a node are simply not detectable by lower layers. Thus, other techniques such as Keep Alive (KA) messages are being used. There is clearly no shortage of KA mechanisms implemented by routing protocols such as OSPF, ISIS or protocols such BFD. KA have their own shortcomings related to their parameter settings: aggressive timings introduce a risk of oscillations of traffic between multiple paths upon missing few KA messages, a real challenge on (lossy) links where packet loss is not negligible, which introduce high risks of oscillations. Once the failure is detected, a plethora of techniques can be used such as Fast IGP convergence (OSPF or ISIS using fast LSA/LSP generation, fast triggering of SPF, incremental SPF to mention a few), MPLS Fast Reroute (using a back 1-hop tunnel for link protection of multi-hop backup tunnels for node protection), IP Fast Reroute (IPRR) or other protection mechanisms used at lower layers (1+1 protection, 1:N, etc.) have proven their efficacy at minimizing downtime. Such recovery technologies have allowed for a fast convergence time in the order of a few milliseconds, while guaranteeing equivalent SLA other alternate paths (e.g., MPLS TE with bandwidth protection).

Unfortunately, there is a large category of failures highly susceptible of impacting application experience that remain largely undetected. The notion of grey failures has been covered in a companion document [grey-failure]. These grey failures may have a high impact on application experience because of packet loss, delay or jitter without breaking the link/path connectivity (and thus they are not considered by the aforementioned technologies as “Failure”). In this case, most -- if not all -- KA-based approaches would fail, leaving the topology unchanged and the traffic highly impacted even though a preferable alternate path may exist.

Existing solutions such as Application Aware Routing (AAR) rely on the use of network-centric probes such as BFD and HTTP probes to evaluate whether a path meets the SLA requirements of an application using a so-called SLA Template. The most common approach consists in specifying some hard threshold value for various network central KPIs such as the delay, loss and jitter averaged over a given period of time (e.g., Delay average computed over 1h should not exceed 150ms one-way for voice). Such templates may be highly debatable and the use of statistical moments such as average and 90th percentile values have the undesirable effect of smoothing out the signal and lose the necessary granularity necessary to detect sporadic issues that impact the user experience. One may then shorten probe frequencies, use higher percentiles but the granularity is unlikely to suffice for the detection Grey failures impacting the user experience.

Still, AAR is a great step forward when compared with the usual routing paradigm, according to which traffic rerouting occurs only in presence of dark failures (i.e., path connectivity loss). Note that AAR is a misnomer since the true application feedback signal is never taken into account for routing; path selection still relies on other static network metrics and SLA templates are a posteriori assessed and verified as explained above. AAR is reactive (the issue must first take place to be detected and must last for a given period of time for a rerouting action to take place) with no visibility on the existence of a better alternate path: rerouting is triggered over alternate paths with no guarantees that SLA will be met once rerouting the traffic.

Lack of Learning in the Internet?

It is an escapable fact: most of the control plane networking technologies do not incorporate learning from the past but rather focus on the ability to react as quickly as possible. Imagine a human brain incapable of learning and rather just reacting. The human brain is without a doubt the most advanced learning engine and the Hebbian theory related to synaptic plasticity has been a key principle in neuroscience. "What fire
together wire together'; thanks to synaptic plasticity neural networks are formed (wire together) dynamically thus allowing us to learn and also unlearn (for example thanks to synaptic downscaling during sleep).

![Image](Image)

**Figure 2 – Brain Predictive Coding across cortical layers**

The brain is also an impressive predictive engine: the simple action of grabbing an object involves a complex series of predictive actions (e.g., just anticipating the shape of the object). As shown in figure 2, some areas of the brain get inputs from other regions, provide predictions that get adjusted according to sensing. Similarities with a predictive Internet will be shown later in the document. Other forms of predictions involving hierarchical structures with interaction between sensing and prediction (in different brain areas communicating via different layers of the neocortex) are also very well-known in vision, auditory pathways. Higher level predictions are known to be performed in the PreFrontal Cortex (PFC).

**How about learning in the Internet?**

As a matter of fact, data has not really been used for designing protocols that are capable of learning. There are some minor exceptions such as packet retransmissions (backoff) at lower layer of transport layers, ability to learn the instantaneous bandwidth along a given path or the use of hysteresis, … Various protocols have adaptive behaviors according to a very recent past, without true learning/modeling. Most control plane operations mostly focus on the ability to react.

**Towards a Predictive Internet**

Quoting Niels Bohr: "It is hard to make predictions, especially about the future". Cisco has invested considerable research to investigate the ability for networks to combine a proactive approach with a reactive approach. To that end, an unprecedented analysis has been made on millions of paths across the Internet, using different networking technologies (MPLS, Internet), access types (DSL, fiber, satellite, 4G), in different regions and Service Provider networks across the world. The objective was first to determine the dynamicity of a vast number of paths, along with application experiences. [internet-dynamics] provides an overview of such analysis. Figure 2 shows a few approaches for data path statistical models.

![Image](Image)

**Figure 3 – Models of Path dynamics in the Internet ([internet-dynamics])**

More advanced models relying on a variety of features and statistical variables have been performed (e.g., spectral entropy, Welch spectral density, MACOS, …) along with their impact on application experience.

The fact that path "quality" across the Internet is diverse and varies over time is not new. But, the main key take-away lies in the ability to quantify across space and time using a broad range of statistical and mathematical analysis. As pointed out earlier, in a cloud, highly virtualized world where the network keeps changing and applications constantly move, it has never been so important to equip the Internet with learning capability.

**What is Prediction/Forecasting?**

Simply put, predicting/forecasting refers to the ability to anticipate events of interest such as failures; thanks to the use of model trained with historical data.

The most common question is "Which algorithm are you using?". Unfortunately, there is no one-size-fits-all, and Predictive Internet undoubtedly relies on a collection of algorithms and technologies used with specific objectives in mind. The forecasting horizon is one of the most decisive criteria. Forecasting with very high time granularity (e.g., months) is extremely smooth and easily captured by simple algorithms. Such an approach is referred to as "trending", simple and robust but of relatively minimal value for forecasting. On the other side of the spectrum, a system capable of forecasting a specific event (e.g., failure) impacting the user experience is far more interesting and challenging. Even for such a well-defined problem, various approaches may be used:

- The time series may first be categorized using hand-crafted criterion applied to various characteristics such as the entropy, Welch spectral density, … using various rules-based and ML-based clustering algorithms,
- Then ML algorithms such as Recurrent Neural Network (RNN) like Long Short-Term memory (LSTM) may be used for forecasting, using local, per-cluster or even global models.

We have also developed other approaches such as State Transition Learning for forecasting failure events by observing the prominent subsequence of network state trajectories that may lead to failure.

Mid- and Long-term prediction approaches ought to be considered whereby the system performs training on historical data and model the network to determine where/when actions should be taken to adapt routing policies and configuration changes in the network in light of the observed performance and state of the network (i.e., Internet behavior). Such predictions then allow for making recommendations (e.g., change of configuration or routing policies) that will improve the overall network SLO and application experience. Mid- and Long-term predictions have proven to be highly beneficial, although less efficient than short term recommendations that deal with short term predictions and remediations. Such systems must take into account a series of risk factors including the stability of the network and traffic pattern in order to minimize the risk of predictions that would be quickly outdated. This contrasts with a short-term predictive engine used for "quick fixes" and avoidance of temporary failures that would be enabled with full automation (a topic that will be discussed in a companion document).

Forecasting accuracy is a recurring topic. Any forecasting system will make prediction errors. However, such a system can be designed so as to make trade-offs between False Positive (FP) and False Negative (FN). FP means that a failure predicted does not occur whereas a FN refers to the opposite situation. For example, a Machine Learning (ML) classification algorithm may be tuned to deal with the well-known Precision/Recall tension where Precision=TP/(TP+FP) and Recall=TP/(TP+FN). In other words, the algorithm must be tuned to favor either Precision or Recall. Cisco’s predictive engine favours Precision...
over Recall, a safe approach for highly minimizing the risk of FP, while with current reactive approach there is no prediction, so the rate of FN=100%. In other words, most prediction of the event should be correct even if all events cannot be predicted.

Many other dimensions must be taken into account in such a predictive system. For example, will the proactive action of rerouting traffic impact the traffic already in place along the alternate path?

In a live system, such as the one Cisco has developed, other criteria must be taken into account and time granularity is of the utmost importance both for telemetry gathering and time to react (triggering close loop control) with tight implications on the architecture.

**Are all failures predictable?**

From a pure theoretical standpoint, yes, since random events are extremely rare in nature, but of course the reality is different. In most cases, events indicative of some upcoming failures usually exist but they are not always monitored by existing systems. Moreover, the timeframe is not always compatible with the ability to trigger some actions (even a fiber cut may be predicted by monitoring the signal in real-time but some nanoseconds before the damage leading note enough time to trigger recovery action, even if a predictive signal exists). In reality, the ability to predict event is driven by the following factors:

- Finding “Signal” in telemetry with high SNR
- Computing a reliable ML model with sufficient Precision/Recall
- Designing an architecture at scale supporting a Predictive approach (this last aspect should not be overlooked; there is a considerable gap between an experiment in a lab and the scale of the Internet).

Predicting consists in finding signals used to build a model and producing a given outcome (e.g., component X will fail within x ms, or probability of failing of component Y is Pb) using classification and/or regression approaches. The ability to predict raises a number of challenges Cisco managed to overcome; thanks to a decade of deep expertise in Machine Learning and analytics platforms.

**Is the Predictive Internet a promising avenue?**

Yes, it is. Such a system has been in production in 100 networks around the world, doing real-time predictions for several months and has proven to perform predictions highly improving the overall network SLO and application experience. Although the details of the exact architecture, telemetry (and technique for noise reduction), algorithms, training strategies are out of the scope of this document, it is worth providing several examples of overall benefits that a predictive system can bring. Figure 4 shows the overall number of minutes with SLA violation observed in a 30-day period on a network (in Red). Next to it are the number of minutes of SLA violation that would have been avoided (“saved”) using the predictive engine, which managed to accurately predict such (grey) failures (application SLA violation) but also finding an alternate free of SLA violation in the same network (without adding any additional capacity).

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**Figure 4:** number of minutes of application SLA violation (red) and number of minutes of SLA violation a predictive system would have avoided (real values in an existing network).

For the sake of illustration, let’s explore examples of such predictions (i.e., SLA violation) that were correctly predicted. The next set of figures show when a failure was predicted (see green dots on the time line). Various time series show after the predictions the loss, delay and jitters. In ocean blue is the default path programmed on the network, in the dark blue color is the path recommended by the predictive engine, thus validating that the prediction was indeed correct.

In the first example Fig 5 (a path between Malaysia and Costa Rica), many minutes of traffic (11,000 minutes of voice traffic) with SLA violation could have been avoided (green) for traffic sent along Business Internet path (ocean blue) by proactively rerouting traffic onto an existing bronze internet path (a priori with less strict SLA) (dark blue).

**Figure 5:** Prediction of SLA violation because of packet loss on a path between Costa Rica and Malesia: 90% of SLA violation avoided.

Figure 6 shows a prediction of packet loss spike (way before they take place) along a short-distance MPLS paths resulting in 82% of SLA violation over a 30-day period.
path (with measures such as the number of minutes of traffic saved from SLA failures) and their variation other times.

Figure 8: Number of minutes of traffic with SLA violation avoided thanks to accurate predictions on six worldwide networks

Figure 8 shows the number of minutes of traffic saved of SLA violation thanks to accurate predictions. The Y-axis shows the regions of the world and X-axis how it varies over time. It can be noticed that the number of traffic saved varies significantly across networks and over time. It is also worth noting that predictions are constantly adjusted thanks to continuous learning: indeed the Internet and other SP networks are highly dynamics and experience failures, new peering agreements take place, SaaS applications do move across the Internet and traffic loads evolve.

Conclusion and Next Steps

Without a doubt, adding learning capabilities to the Internet will increase the overall network SLO and application experience and may arguably be overdue. Real data driven experiments have shown that such an approach will complement the reactive approach that has governed the Internet for the past four decades. Although there is no one-size-fit-all approach, various statistical and ML driven models have shown the possibility to predict future events and take proactive actions for short-term and long-term predictions with high accuracy, avoiding a high number of failures that would have significantly impacted the user experience. The path towards a Predictive Internet will take place over several years and is far from being over but coupled with Autonomous networks (Self-Learning/Healing networks), this approach could be one of the most impactful technologies for the Internet. Many more innovations are in the works.

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References

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