

# Demo: SONVer: SON Verification for Operational Cellular Networks

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**Abstract**—The Self-Organizing Networks (SON) concept includes the functional area known as self-healing, which aims to automate the detection and diagnosis of, and recovery from, network degradations and outages. Changes to the configuration management (CM) parameters for network elements could be a cause for degraded network performance and stability; hence, the verification of their effects becomes crucial. In this paper, we present SONVer, a tool that performs SON verification, using anomaly detection and diagnosis techniques that operate within a specified spatial scope larger than an individual cell [1]. SONVer automatically classifies the state of the network in the presence of CM changes, indicating the root cause for anomalous conditions. SONVer uses Key Performance Indicators (KPIs) and CM history from real cellular networks to determine the state of the network; visualize anomalies at a large scale; and identify the causes of anomalies and the group of cells that were affected.

**Index Terms**—network automation, self-organized networks (SON), SON verification, anomaly detection, diagnosis

## I. INTRODUCTION

Self-Organizing Networks (SON) [2] offer increased automation and optimization for network operations through mechanisms such as self-configuration, self-optimization and self-healing. In this paper, we focus on demonstrating SON verification capabilities, as part of self-healing. SON verification aims to prevent network-level degradations, by verifying the effects of changes in network element configurations. SONVer builds on and demonstrates previous work [1] in analyzing Key Performance Indicators (KPIs) and Configuration Management (CM) history to determine the state of a network and whether CM changes cause any performance degradations. SONVer uses a network-level anomaly detection component to detect anomalies in the overall network scope based on KPI measurements. When anomalies are identified, they are further analyzed by the diagnosis component, which considers correlations between KPI changes and CM changes. Moreover, SONVer facilitates the exploration of the state of the network as well as the results of the detection and diagnosis components.

## II. SON VERIFICATION

Our SON verification framework [1] aims to prevent network-level degradations that are due to network-element configuration changes. The verification is a hard problem as mobile broadband networks are highly complex, changes can

be inflicted either in an automated or manual fashion, and there are no simple indicators for the overall health of the system. Our approach addresses the problem of verifying the effect of network configuration changes by monitoring the state of the network and determining if degradations are due to CM changes performed prior to the verification process. Our framework has two main components: 1) a network-level anomaly detector, which monitors group of entities (i.e., cells) using topic modeling [4] combined with 2) a diagnosis component, which uses Markov Logic Networks (MLNs) [3] to generate probabilistic rules that discern between different causes.

Topic modeling [4] was initially used for discovering topics in documents, where a topic is defined as a probability distribution over words. Each topic is individually interpretable and characterizes a coherent set of correlated terms, corresponding to a network state for our context. Topic modeling is applied to KPI data from all the cells in scope and generates topic modeling clusters, which are further classified by a semantic interpretation module as either normal or abnormal, based on KPI semantics. Using the labeled clusters, the overall state of the network at a point in time, is determined by a mixture of weights for the different clusters. While the topic modeling component does not have any *a priori* notion of the types or numbers of network states, it determines them automatically (applying a Hierarchical Dirichlet Processes (HDP) [5] topic modeling approach).

The Markov Logic Network (MLN) [3] is an approach for probabilistic reasoning using first-order predicate logic. In traditional first-order logic, hypotheses can be described in terms of supporting evidence and conclusions about network properties. Additionally, MLNs also permit rule weighting and an explicit representation of the probabilities associated with logical statements. The MLN-based diagnosis component is triggered only in case of abnormal behavior. The MLN inference is achieved by using CM change history information in form of an event sequence, along with the MLN rules and their associated weights. The MLN rules can be generated based on human expert knowledge or they can be learned, along with the weights associated with each rule.

### III. SONVER TOOL

SONVer uses a main dashboard (Figure 1), which enables the user to investigate the state of the network, visualize anomalies that happen at a large scale (network and Radio Network Controller (RNC) level), understand the causes of anomalies, and identify the cells or group of cells that were affected. The dashboard has the following components:

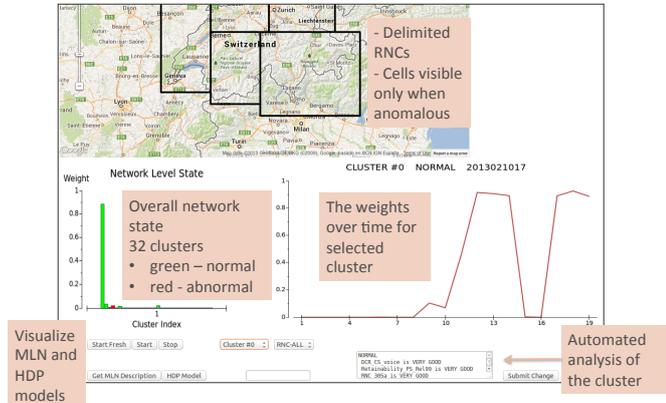


Fig. 1. SONVer main dashboard, which enables the investigation of the network states as clusters.

- At the top of the dashboard, the map annotation indicates what area is in focus with the analysis. In the example in Figure 1, we notice that there are squares marked on the map. The squares correspond to different RNCs, each of which can be investigated individually. In Figure 1, the focus is on all the network data. The user will have the alternative of selecting only an RNC as the interest area. When the topic modeling approach determines that an anomaly is exhibited, the MLN method further investigates the hypothesis for anomalous events and highlights on the map the cells that are affected by that condition. In Figure 2, the red dots on the map illustrate the cells that exhibit the anomalous behavior due to CM changes determined by the MLN approach. We notice that the map has a set of annotations that clearly point to the corresponding hypothesis. Moreover, SONVer allows the user to investigate the MLN model.

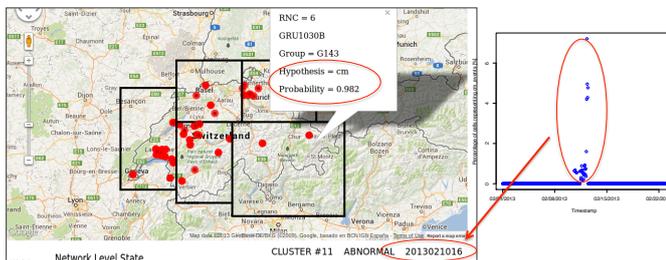


Fig. 2. Investigating anomalous cells due to CM changes.

- The graph to the left allows the user to assess the state of the network as a whole. The graph illustrates the weights of all clusters generated by the topic modeling at each

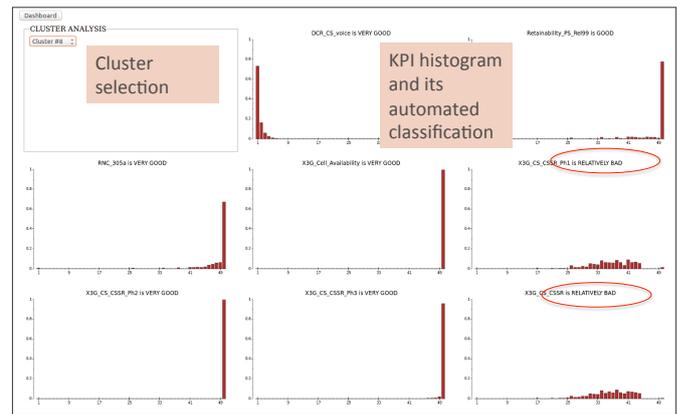


Fig. 3. Cluster analysis

timestamp (e.g., if KPI data is generated at a rate of 1 hour, this graph would change every hour to indicate the current state of the network). The sum of all weights is always 1; consequently, the weights indicate the percentage of the cells that behave in conformance with the corresponding cluster. The green bars correspond to normal clusters, while the red bars to abnormal clusters.

- The graph to the right allows the user to navigate through all the weight time series for individual clusters. This component provides the user with the ability of understanding when the state of the network changed and how severe the change is. Moreover, below the graph there is a text field, which allows the user to investigate the automatically generated labels for each cluster (normal vs. abnormal) along with the details on each KPI. The user has the ability to annotate the labels, given the cluster analysis component, which appears as a new page with all the cluster histograms for each KPI (Figure 3).

Our demonstration will capture all these features applied to real cellular network data and will adapt in real-time to scope changes.

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### REFERENCES

- [1] Gabriela F. Ciocarlie, Christopher Connolly, Chih-Chieh Cheng, Ulf Lindqvist, Szabolcs Nováczki, Henning Sanneck, MuhammadNaseer-ul-Islam, Anomaly Detection and Diagnosis for Automatic Radio Network Verification, Submitted to the 6th International Conference on Mobile Networks and Management (MONAMI), 2014.
- [2] S. Hämäläinen, H. Sanneck, and C. Sartori (eds.), "LTE Self-Organizing Networks (SON): Network Management Automation for Operational Efficiency," Wiley, 2012.
- [3] Richardson, Matthew, and Pedro Domingos. Markov logic networks. In Machine learning, vol. 62, no. 1-2, 2006, pp. 107-136.
- [4] M. Steyvers and T. Griffiths. Probabilistic topic models, Handbook of Latent Semantic Analysis, Erlbaum, 2007.
- [5] Yee Whye Teh, Michael I. Jordan, Matthew J. Beal and David M. Blei (2006). Hierarchical Dirichlet Processes. Journal of the American Statistical Association 101, 476: 1566-1581.