Monitoring System for Carrier Grade MESH Networks

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Abstract: The paper presents a monitoring system for carrier grade mesh networks. First, the system architecture, components and interfaces are described. Then the measured and discovered network parameters are discussed. A link prediction and trigger algorithm based on a modified mean-reverting diffusion process is proposed. The results from analysis show that this function can significantly enhance link reliability.

Keywords: mesh networks, monitoring system, IEEE 802.11, data analysis.

1. Introduction

Monitoring and performance management are critical for network operators as they have a direct impact on competitiveness and profitability. Network-wide visibility is vital to ensure that service delivery and quality of experience are complying with Service Level Agreement (SLA). A carrier-grade network monitoring not only enables real-time system performance, fault tracking and resolution, but also provides operator the knowledge on when to upgrade the network. In addition, the system requires dynamic self-monitoring and configuration capabilities in order to support CaRrier grade Mesh Network (CARMEN)'s vision in reducing deployment and operational costs.

For a heterogeneous system, the main role of monitoring system is to supply other modules accurate and timely information regarding the status of network, in both technology-dependent and technology independent manner. Depending on the monitored parameters, different sampling techniques, as well as statistical analysis and data-storing methods are to be considered to optimise the monitoring performance in terms of data accuracy and reduction of monitoring overhead. Aggregation, correlation and statistical analysis of the gathered data on different timescales is essential for tracking and keeping up-to-date the states or information of the mesh network. Reports from the monitoring system are not only crucial for self-configuration and planning functions, but also important for the dynamic resource management, such as routing updates or quality of service (QoS) including admission control decisions.

2. CARMEN Architecture

The overall architecture of the CARMEN Mesh Network with respect to main functional block of monitoring system is presented in Figure 1. It consists of several Carmen Mesh Points connected to the core network via a number of Carmen Gateways (CGW) [1]. CGWs, which act as gateways are typically connected to the core network via a wired connection. Other nodes CARMEN Mesh Nodes (CMNs) are interconnected via radio links operating on different or shared frequency channels. In case of different channels operating mode, more than one physical interface is required or virtualization mechanism of the interface should be implemented. In order to achieve the carrier grade mesh intercommunication, each wireless mesh network node performs continuous measurements and monitoring of several radio parameters. Gathering, processing and monitoring of measured data allows us to create an additional decision plane. It introduces enhancements to the existing functionality of Routing and Self-Configuration Functions and supports their decision criteria. The main benefit of monitoring-based decision making process should be reflected in better accuracy of routing tables, and efficient spectrum allocation, which allows interference avoidance [1]. The Monitoring system allows us to create a map of mesh links topology, track links' parameters changes and provides prediction mechanism of link behaviour, which allows to re-configure network in advance and to improve mesh network reliability. Such an additional decision plane allows introducing cross-layer optimization mechanisms of existing mesh network in the context of cognitive network architecture [2], due to the fact that monitoring system aims to be an aggregator for abstracted, different background wireless technologies. Especially long term monitoring of wide variety of radio related parameters with addition of L2/L3 characteristic provides an additional feedback loop [3] for all decisions taken in response of short-term radio environment behaviour (i.e. link reconfiguration upon triggered alert), which can result with avoidance of traffic redirection via unstable links and their further reconfiguration.

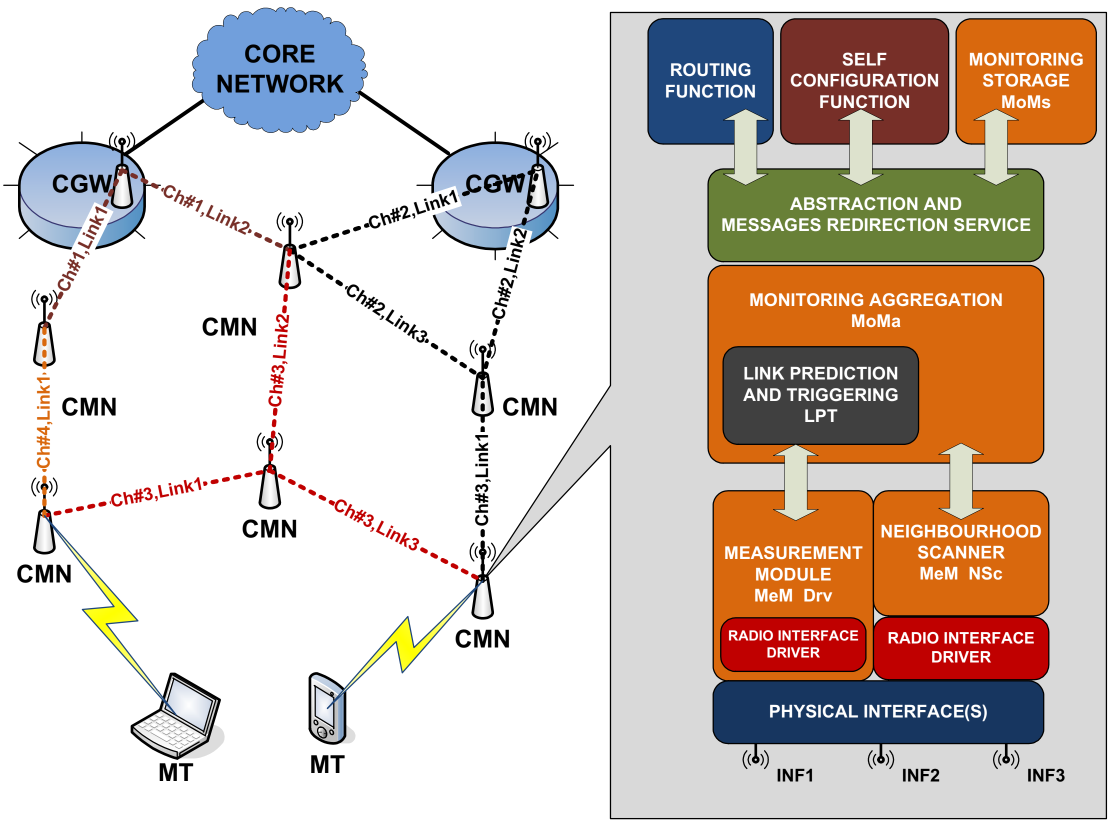

Figure 1. Carmen Mesh Network Architecture.

3. Methodology

The Carmen Mesh Network Monitoring System assumes two main areas of operation. On one hand it should precisely monitor the behaviour of logical links (described by source and destination EUI_64 addresses) originating or ending on current physical interface used for regular transmission. This is directly related to monitoring of L2 frames and their parameters within a radio channel, the physical interface is configured to work on. On the other hand, a more generic view of neighbourhood is also required to satisfy Self Configuration optimisation of radio coverage and resources assignments functionalities. Thus a frequency scanning procedure has been introduced in order to support network bootstrap phase and to detect any new CMN. The scanning procedure is based on discovery of potential radio links which can be created within a mesh network. Fast variations of radio channel characteristics entail the need of smoothing mechanism introduction to deal with raw data measurements, as well as to avoid incorrect decisions based on temporary measured values of parameters. To overcome this problem, a double level averaging process has been implemented within a measurement modules and monitoring aggregation module as well. Additional long-term statistics repository has been created to provide feedback mechanism for routing with link stability description. Also link related events are predicted and reported by link triggering and prediction module.

The main problem related to data plane monitoring and frequency sweeping procedure is their strong physical interface dependency. The neighbourhood scanning should be done constantly and looped over a set of radio channels and thus requires a dedicated interface. However it is possible to merge both measurement schemes over a single interface but that would require extra coordination for example to perform a full neighbourhood scanning during the node/network bootstrap phase in order to get an initial view of the neighbourhood or to scan during transmission gap intervals.

4. Technology Description

The architecture of the Monitoring System with its main components and interfaces is depicted in Figure 2 and we will describe each of the modules in the following subsections.

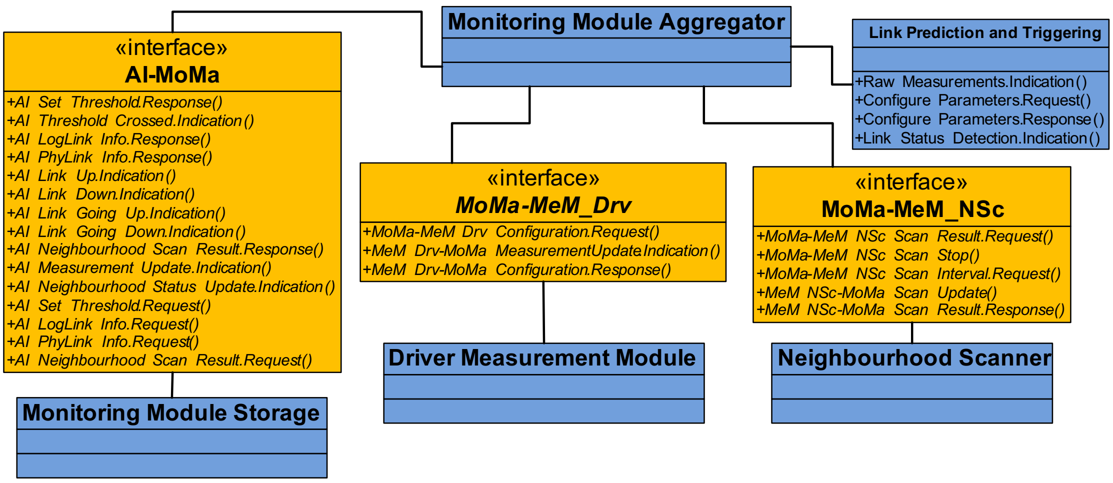

Figure 2. Monitoring system components and interfaces.

4.1 Driver Measurement Module

Driver Measurement Module (MeM_Drv) is a module which exists within the modified MadWiFi driver of the wireless interface devoted to regular data transmission [4]. This module is implemented directly in the driver because it is responsible for measurements of number of L1, L2, and L3 parameters based on the transmission and reception of IEEE

802.11 frames and their preambles/headers. These measurements and calculations are performed along with the activity of the wireless card and reported periodically according to configuration from Monitoring Module Aggregator (MoMa). MeM_Drv deals with strongly technology specific data within the time-scale of microseconds. The overall statistics are available for the entire traffic of each wireless interface. Idle intervals, when there is no transmission in wireless medium, are also counted into reports. This module has one direct interface to MoMa module used for both: MeM_Drv configuration and transmission of reports. Single interface is reasonable and it allows for an improved stability during the implementation process. MeM_Drv supports IEEE 802.11 a/b/g/e standards. The list of parameters recognized and measured by MeM_Drv for every wireless interface is presented in Table 1.

Table 1. The list of parameters recognized and measured by MeM Drv

Recognized parameters	Measured parameters
1. Preamble type	1. Number of active nodes in the neighbourhood
2. Service Set Identifier (SSID)	2. Number of received frames
3. Channel	3. Number of transmitted frames
4. Supported rates	4. Frame Error Rate (FER)
5. Frame type	5. Bit Error Rate (BER)
6. Sender/Receiver MAC address	6. Per class and overall uplink delay
7. Priority of received frame	7. Physical layer (L1) throughput
8. Frame length	8. Data link layer (L2) throughput
9. Timestamp of Rx/Tx frame	9. Network layer (L3) throughput
10. Correctness of received frame	10. Link occupancy defined in %
11. Signal to Noise Ratio (SNR) – tech independent or RSSI – tech dependent	11. The remaining L1/L2/L3 link capacity

4.2 Measurement Module for Neighbourhood Scanning

Measurement Module for Neighbourhood Scanning (MeM-NSc) is a module used to detect active neighbour nodes' interfaces and to send the information about detected nodes' interfaces to the MoMa module. A scanning procedure is initiated on MoMa request using MoMa-MeM_NSc interface messages. The detection procedure of neighbour nodes is based on scanning 802.11 channels for packets sent from neighbour nodes' interfaces. Channel swapping algorithm is controlled by a Scanning scheduler module. To capture 802.11 MAC frames in real time MeM_NSc a PCAP library is used. A Packet analyser module of MeM_NSc has access to all fields of captured MAC frames and parameters. Following parameters are chosen to characterise detected interfaces: MAC address, SSID, antenna signal, antenna noise, Signal to Noise Ratio (SNR) or Received Signal Strength Indication (RSSI), transmit power, operating channel number, capability field from 802.11 MAC header, supported rates, out frames count, in frames count, average frames rate, average data frames rate. Based on captured frames analysis MeM_NSc generates following statistics parameters of each scanned channels: channel utilization, frames error rate, frames Bit Error Rate (BER), detected frames count. For bootstrap and control of overall behaviour of MeM_NSc a Controller module is responsible.

4.3 Monitoring Module Aggregator

Monitoring Module Aggregator (MoMa) is a module designed for gathering measurement related data and to process and convert this data into different time scale domain. Measurement Modules are capable of taking measurements of both physical and logical links behaviour and to report their current states, but accordingly to the character of fast variable radio statistics in the range of milliseconds their outcome needs to be aggregate and smoothed out. The Monitoring Module Aggregator receives raw measurement data from both Driver Measurement Module (MeM_Drv) and Neighbour Scanner (MeM_NSc), as well, in both: on a request and on a change manner using MoMa-MeM_NSc and MoMa-MeM_Drv interfaces (see Figure 2). Statistically processed data is simultaneously updated and stored to be passed on request to the upper modules such as: Routing Function (RtF) and Self-Configuration Function (SCF) via AI-MoMa interface. Some data is periodically recorded in a Monitoring Module Storage (MoMs), which is a long-term links characteristic repository. As an addition the trigger-based operational mode is also possible for any module which will register for a trigger-based service, which is devoted for constant monitoring of a desired parameter until the pre-set threshold is being crossed. In such a case the Monitoring Module Aggregator generates a proper indication to notify the service registered entity. Based on pre-processed measurement data the Monitoring Module Aggregator creates the information for neighbourhood topology discovery functionality.

The Link Prediction and Trigger (LPT) submodule which reside inside MoMa determines state change and predictive events such as *Link up* (LU)*, Link Coming Up* (LCU)*, Link Going Down* (LGD), *Link Down* (LD) as defined in IEEE 802.21 [5]. The LGD event in particular help wireless nodes to prepare for link switching prior to link down so that switching delays and service interruptions can be minimized. In mesh environment, the reliability of wireless backhaul links is extremely critical as any link disruption may affect more than one node. For that reason, such predictive triggers are particularly important to ensure carrier-grade performance. An analysis of our proposed link prediction algorithm is presented in section 5.

4.4 Monitoring Module Storage

After data pre-processing, selected measurements are transferred to Monitoring Module Storage (MoMs), where link descriptions and their average characteristics are available for Self Configuration module in a longer timescale (e.g. hours or days). Further analysis of the frequency of appearance of links in a longer time-scale can eliminate unstable links. The long-time data repository could enhance Routing Function with link reliability to be included as a parameter for composite metric.

5. Link Prediction and Trigger Analysis

To make reliable forecast of RSSI values of local and neighbouring mesh links, here we would build diffusion process models for a selected window size of a series of RSSI values. The prediction can be applied to any channel info received from the neighbouring radios. Using a time step of 100ms, the following Figure 3 shows both the time series of raw and smoothed RSSI values of a typical link down event. The latter is smoothen via moving average method with an average of 10 values in order to reduce short term fluctuations. Here the RSSI link down (LD) threshold value is set at -80 dBm and link going down (LGD) threshold is set as -76 dBm following the criteria set by Intel [6].

Since RSSI values do exhibit mean-reverting behaviour (converging towards a long term mean), it is natural for us to look at models with this property. One such stochastic model which we are considering in this paper is the Ornstein-Uhlenbeck (OU) diffusion process which was first applied in physics [7] to describe Brownian motion of particles suspended in a fluid with friction. In this paper due to the inherent jump properties of RSSI values we propose modelling the values using a modified mean-reverting diffusion process called the Ornstein-Uhlenbeck jump diffusion process, $OU(\kappa,\theta,\sigma,J)$, defined by the stochastic differential equation (SDE) :

$$dX_t \quad \kappa(\theta \quad X_t)dt + \sigma\, dW_t + \log J_t\, dN_t$$

where $dW_t \sim N(0, dt)$ is a Wiener process, $\kappa > 0$ is the mean reversion rate, θ is the mean and $\sigma > 0$ is the volatility.

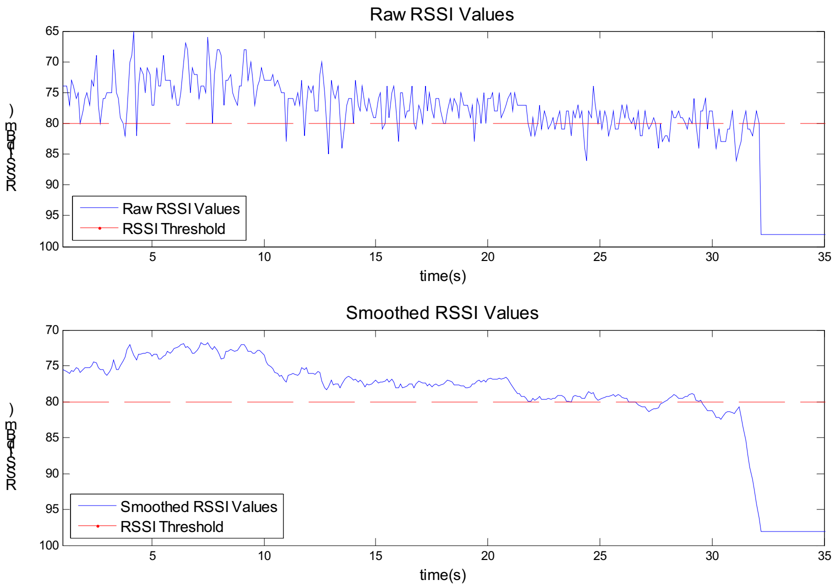

Figure 3. Time series of raw and smoothed RSSI values

The process dN_t is a Poisson process with parameter λ such that

$$dN_t = \begin{cases} 1 & \text{with probability} \quad \lambda\, dt \\ 0 & \text{with probability} \quad 1 - \lambda\, dt. \end{cases}$$

The random variable $J_t > 0$ is the jump amplitude with $\log J_t \sim N(\mu_J, \sigma_J^2)$, and dW_t, dN_t and J_t are mutually independent. Using the analysis given by [8] for each forecast step ahead $\ell \geq 1$ and a constant time step Δt we can solve the SDE as

$$X_{t+\ell\Delta t} = X_t e^{-\kappa\ell\Delta t} + \left(\theta + \frac{\lambda\mu_J}{\kappa}\right)\left(1 - e^{-\kappa\ell\Delta t}\right) + \sigma\sqrt{\frac{1 - e^{-2\kappa\ell\Delta t}}{2\kappa}} Z_1 + \sqrt{\frac{\lambda}{2\kappa}\left(\mu_J^2 + \sigma_J^2\right)} Z_2$$

with

$$E(X_{t+\ell\Delta t}) = X_t e^{-\kappa\ell\Delta t} + \left(\theta + \frac{\lambda\mu_J}{\kappa}\right)\left(1 - e^{-\kappa\ell\Delta t}\right), Var(X_{t+\ell\Delta t}) = \sigma^2\left(\frac{1 - e^{-2\kappa\ell\Delta t}}{2\kappa}\right) + \frac{\lambda}{2\kappa}\left(\mu_J^2 + \sigma_J^2\right)$$

where Z_1, $Z_2 \sim N(0,1)$ and Z_1, Z_2 are independent. Once the parameter values $\hat{\kappa}$, $\hat{\theta}$, $\hat{\sigma}$, $\hat{\lambda}$, $\hat{\mu}_J$ and $\hat{\sigma}_J$ are estimated (see [6]), we can then deduce the estimated forecast $\hat{X}_{t+\Delta\ell}$ follows

$$\frac{\hat{X}_{t+\ell\Delta t} - E(\hat{X}_{t+\ell\Delta t})}{\sqrt{Var(\hat{X}_{t+\ell\Delta t})}} \sim N(0, 1).$$

Based on the forecasted RSSI values of the current mesh link and in order to minimize the error of decision making, Intel [6] introduces a protection margin (or hysteresis factor) $\Delta \geq 0$. The purpose of having this protection margin is to augment it to the RSSI threshold value, $\overline{X}$ so that the link has an enhanced threshold value, $\overline{X} + \Delta$ to ensure a better QoS. Here we define the value $\overline{X} + \Delta$ as the link going down (LGD) threshold and if the forecasted RSSI value is greater than the LGD threshold value, then the system would not trigger a switchover process to another mesh radio. Otherwise the mesh node would trigger a switchover from its current link to a new alternative neighbouring mesh radio provided the RSSI of that radio is good enough. With this protection margin Δ, for a forecasted RSSI value $\hat{X}_{t+\ell\Delta t}$, the probability in making a trigger at time t is defined by:

$$P(\hat{X}_{t+\ell\Delta t} \leq \overline{X} + \Delta) \quad P\left(Z \leq \frac{\overline{X} + \Delta \quad E\left(\hat{X}_{t+\ell\Delta t}\right)}{\sqrt{Var\left(\hat{X}_{t+\ell\Delta t}\right)}} \right) \geq \alpha$$

where $\alpha \in (0, 1)$ is a margin error.

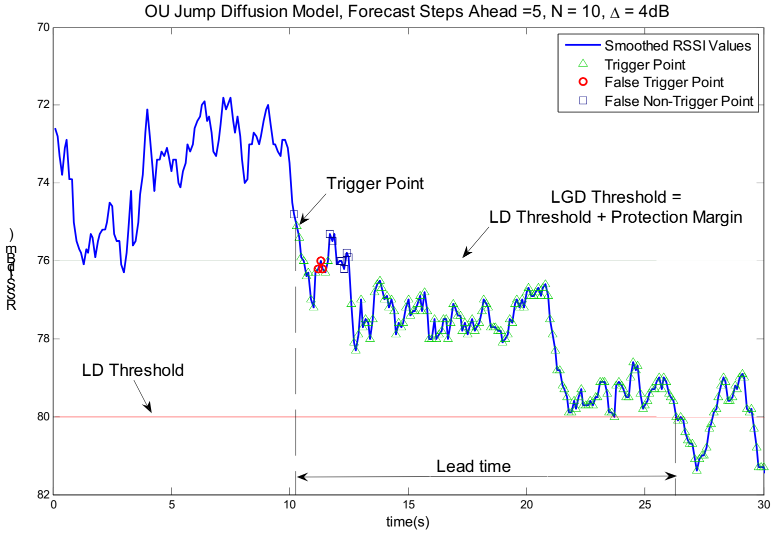

Figure 4. Triggering times of smoothed RSSI values with respect to LGD and LD status

In Figure 4, using $N = 10$, $\ell = 5$, $\Delta \quad 4$dB and $\alpha = 0.60$, we show the performance of our proposed algorithm between the time period 0s to 30s. From the figure we can see the prediction mechanism is able to issue a trigger at a very early stage in preparation before the smoothed RSSI values fall below the LGD threshold. Furthermore the presence of small number of false trigger (or false alarm) and false non-trigger (or missed trigger) attest the suitability of modelling the RSSI values as a stochastic process.

Table 2. Trigger results of OU jump diffusion process and linear regression models.

	OU Jump Diffusion Model	*Linear Regression*
Percentage of Triggers (%)	*66.86*	*65.44*
Percentage of False Triggers (%)	*1.27*	*3.46*
Percentage of Non-Triggers (%)	*33.14*	*34.56*
Percentage of False Non-Triggers (%)	*7.69*	*13.11*
Lead Time (seconds)	*16.1*	*16.3*

In Table 2 we show the comparison of trigger statistics between OU jump diffusion and linear regression methods. From the table we can see that using our proposed method there is a significant improvement in reducing the rate of committing false trigger and false non-trigger as compared with the conventional linear regression method which is a brute strength method without taking into account of modelling fat-tails distribution. Although both methods have comparable lead time which is the time difference between the first successful trigger until the signal strength goes below the LD threshold, by reducing the chances of making a false trigger or missed trigger, the proposed algorithm is by far a more reliable method than linear regression. Hence from the success of this trigger analysis we feel that our proposed method would certainly provide future directions on how link prediction issues are solved in the future.

5. Conclusions

In the paper the architecture of monitoring system designed within the ICT CARMEN project has been presented. The monitoring system in carrier grade mesh networks is critical for performance management which has a direct impact on network operator competitiveness and profitability. The main application areas of monitoring system are to discover network topology during network bootstrap and monitor link parameters in real-time. Short term monitoring parameters are used to provide information about status of the network, and to predict links quality parameters. The results of prediction are used to reconfigure the network in advance to avoid service disruption. The first measurement results of prediction algorithms give promising results which will be evaluated in real testbed. Long term monitoring parameters are proposed to use as metrics in a routing protocol and the base knowledge when to upgrade the network. The next steps will cover integration and assessment of monitoring functionality into real testbed of CARMEN network.

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