CygNet MaSoN: Analytics and Machine Learning Enabled Management System for 5G Networks

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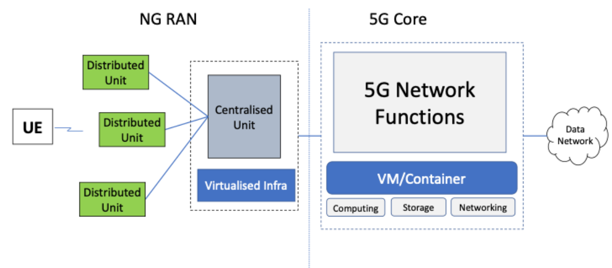
***Abstract*—Autonomous Networking is expected to be the mode of functioning by future networks, including 5G wireless networks. This requires intelligent data analytics and cognitive capabilities to be inherently supported as part of the networking functions, in addition to the current capabilities such as automation and correlation. This demonstration presents CygNet MaSoN, a management system that integrates multiple instances of radio access and core network functions of 5G networks supporting advanced aggregation and analytics features. This system continuously collects critical data related to network and system events, performance measurements and key performance indicators (KPIs) in real-time. It then uses the associated machine learning system to provide insights on network behaviour, estimation of service quality/experience and prediction of probable future network problems. Some of the analytics and machine learning use cases related to 5G networks and implemented on the MaSoN system are also described.**

I. Introduction

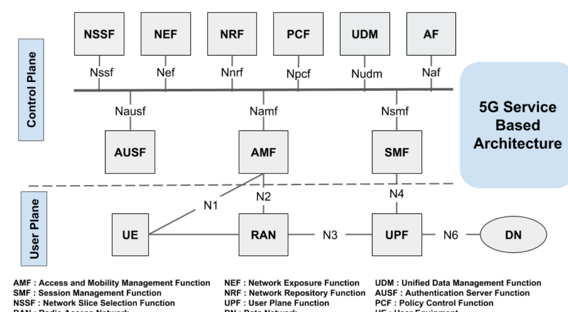
5G wireless networks are expected to play an important role in the type of future networks [1]. The 3GPP standards architecture proposed for 5G networks includes New Radio (NR), Next-Generation Radio Access Network (NG-RAN) and 5G Core, as shown in Fig. 1. 5G networks are built around softwarized and virtualized network functions which can be deployed in data centres and cloud environments for handling such requirements. Management and Orchestration aspects of the Virtualized 5G networks have been based on ETSI Network Functions Virtualisation Management and Orchestration framework (NFV MANO) [2] architecture specifications.

5G networks are expected to support autonomous networking capabilities, where the management system has to continuously monitor network behaviour and performance in real-time and trigger automatic configuration changes to overcome any present and probable future network problems. These new capabilities would have to be built using advanced real-time analytics and machine learning (ML) based techniques so that human intervention and dependency is minimized. Management and Orchestration for 5G networks have to support such capabilities to achieve the expected functioning of future networks.

We have developed a system called CygNet MaSoN (Manager for Softwarized Networks) that supports such capabilities and will be demonstrated at the conference. MaSoN is expected to be one of the critical components of the Indigenous 5G Testbed project [3] management function and also for management of future 5G networks in potential service provider environments. Apart from supporting current capabilities of automation and correlation in management systems, this system will have in-built analytics and machine learning capabilities to meet the autonomous networking requirements. In this work, details on the use cases currently implemented namely prediction of anomalous 5G Core User



(a) 5G Network Components



(b) 5G Core Service-Based Architecture

Fig. 1: An overview of the 5G Architecture.

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CygNet is the brand of OSS/NMS products from NMSWorks Software

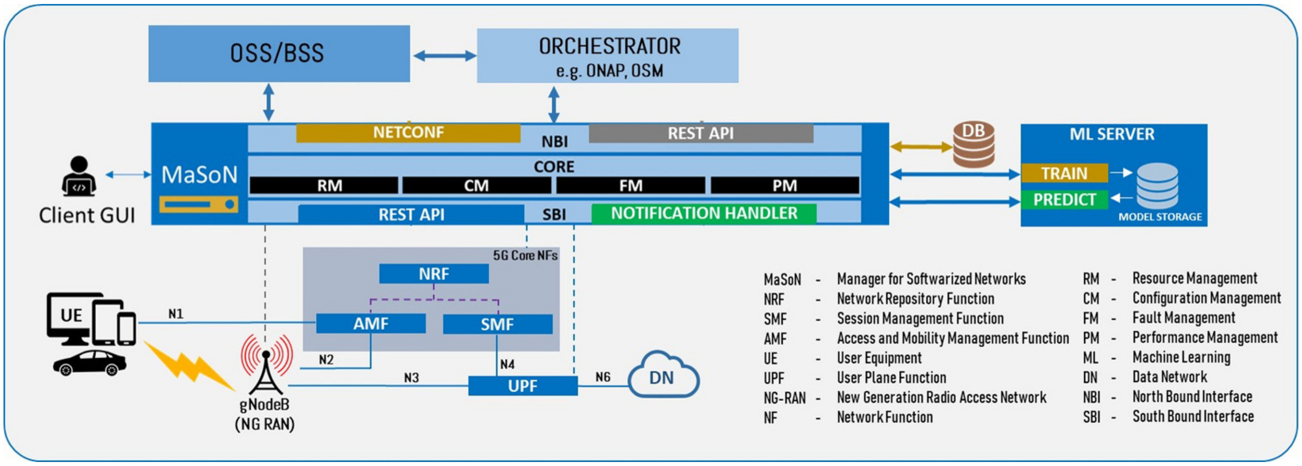

Fig. 2: CygNet MaSoN Architecture

Plane Function (UPF) behaviour based on monitoring its N3 interface PM KPIs and traffic load prediction for 5G cells by monitoring cell-wise traffic utilization, number of users and recent connection requests are described.

II. CygNet MaSoN Architecture

CygNet MaSoN is a management system providing the Element Management (EM) functionality for the network functions and also part of the Network Management functionality for 5G networks. The architecture of MaSoN is shown in Fig. 2. It is a unified management layer (which is specified as the EM component in ETSI NFV MANO architecture) across the 5G RAN and the 5G-Core xNFs (Virtual Network Functions: VNFs & Physical Network Functions: PNFs) providing functions such as Resource Management (RM), Fault Management (FM), Performance Management (PM) and Configuration Management (CM).

In order to perform the above functionalities, MaSoN provides a South Bound Interface (SBI) that integrates with the NFs over the RESTful API. It supports a North Bound Interface (NBI) for integration with the Orchestration systems (e.g. Open Network Automation Platform: ONAP [4], Open Source MANO: OSM [5]) and Operations Support System (OSS) to publish the correlated faults/events and to support retrieval of aggregated performance data and resource information over REST API. It also supports a NETCONF interface for configuration management. In addition, it exposes the processed analytics data to Orchestration systems and OSSs so that they can process and take high-level coordinated actions.

MaSoN aggregates data collected from various functions and components in a 5G network which is stored in its database and presented to the users. In addition, MaSoN supports analytics and ML capabilities to provide advanced insight and automation features as value addition for 5G network management. These include detection of degradation in network performance, predication of anomalous network behaviour, prediction of service quality and resource optimization which are published and also used to suggest and recommend corrective actions to overcome the problems identified. MaSoN has an associated ML Server component which supports training multiple ML Models (includes Deep Learning models and Reinforcement Learning RL models) based on data collected for the different use cases and also prediction of network problems and anomalies using the models.

The ML server component supports multiple implementations for ML use cases related to 5G networks which are developed using ML algorithms such as Regression, Support Vector Machines (SVM), k-Nearest Neighbors (kNN), K-Means Clustering, Random Forest and Artificial Neural Networks (ANN). The ML server is built as a deployment platform using libraries such as Scikit-learn [6], TensorFlow [7], PyTorch [8] which support the ML algorithms. It supports deployment in containers like docker which can be deployed in distributed manner and in cloud environments. It supports continuous and online training for the ML use cases. REST API for training and prediction using JSON as the data format for information exchange is also supported.

Since MaSoN has aggregated data across multiple RAN NFs and Core NFs, it supports analytics and ML capabilities that span multiple network functions and segments from a management perspective. Hence, it is aimed to complement and not replace Network Data Analytics Function (NWDAF) which is specified as a Core NF in 3GPP specifications.

III. 5G Analytics and ML Use Cases

Sample analytics and ML use cases for 5G networks implemented using the above architecture are described below.

Use Case 1: Identification of UPF Anomalous Behaviour – User Plane Function (UPF) in 5G Core handles the data plane processing for the 5G wireless networks. It serves as the interconnect point between the radio access and data network portions of the overall network structure. It provides packet routing and forwarding functions along with per-flow QoS handling. The N3 interface in UPF is responsible for the communication between RAN (gNodeB) and the UPF, as shown in Fig. 1.

In this use case, any anomalous behaviour in the functioning of UPF is identified by monitoring the PM KPIs from N3 interface. The anomalous UPF behaviour is identified when a subset of the PM KPIs show abnormal change in their measurements. Selection of N3 interface PM KPIs is done such that their values have strong correlation and when there is sudden uncorrelated change, it indicates abnormal behaviour.

The list of UPF N3 interface KPIs (defined in 3GPP specification 28.552 [9]) selected for this use case, where packets correspond to GPRS Tunnelling Protocol (GTP), are: (i) Data volume of incoming GTP data packets per QoS level from RAN to UPF; (ii) Incoming GTP Data Packet Loss; (iii) Average Uplink (UL) GTP packets delay in UPF; and (iv) Link utilization.

MaSoN continuously collects the data for the above PM KPIs from UPF and sends the latest set of data to the ML server which would identify whether the measured values represent any anomalous behaviour. Anomaly detection approaches such as Multivariate Gaussian Distribution (MGD), Local Outlier Factor (LOF), Isolation Forest, Robust Covariance were implemented in the ML server where they had been trained with initial data to build ML models which are used for prediction of anomalous behaviour as and when new data gets collected. The identified anomalies are stored in database, presented in MaSoN client GUI and notified to the user.

Performance Results – For testing the implemented approaches and comparing the results obtained, simulated data was generated which contained 10,100 entries out of which 100 entries (1% of total entries) correspond to anomalous data. The total entries was split into training data which contained 8000 entries (which includes 50 anomalies) and test data which contained 2050 entries (which includes 50 anomalies). Considering N3 interface speed is 100 Gbps having 1% packet loss and 50 ms round trip time, each entry contains data for the 4 PM KPIs where the range of values used for data generation for normal values were 0 to 80,000,000 kilobits for data volume, 0 to 10,000 packets for packet loss, 5,000 to 50,000 microseconds for round trip time and 0 to 80 for link utilization. Any value that exceeds the maximum value in the above ranges was considered abnormal.

The simulated data was generated for Guaranteed Bit Rate (GBR) which is typically used for conventional voice traffic, Non-GBR which is typically used for internet traffic or OTT voice and video traffic and delay critical GBR type which is typically used for Automation related traffic by using suitable range for the PM KPIs corresponding to those QoS levels. For the above anomaly detection approaches, the F1 score (which has value between 0 and 1) was measured. From the results obtained, it was observed that the MGD approach resulted in the maximum F1 score which indicates comparatively better performance. For the test data evaluated, MGD approach was able to identify all the abnormal entries accurately.

Use Case 2: Prediction of Traffic Load in 5G Cells – Due to varying traffic patterns observed in different regions of a 5G network, the need for efficiently utilizing 5G network resources becomes even more critical. The access portion of the 5G network is divided into multiple cells with base stations deployed to serve the traffic from those cells. Due to dynamically varying traffic load that gets handled in such cells, the possibility of some cells being overloaded and some cells being under-utilized arises.

The objective of this use case is to continuously monitor the traffic load in all cells which is used to predict the traffic load in near term and long term to provide suggestions for load balancing among cells and suggestions for cell splitting and/or merging. This would help in proactively configuring the network for handling the future traffic load. The traffic load data would be continuously processed for providing the possible suggestions so that the network is effectively utilized with the available resources.

Apart from the continuous measurement of cell-wise traffic load and utilization, the implementation monitors and measures the number of User Equipment (UEs), number of Radio Resource Control (RRC) connection requests and active number of radio bearers for each cell. Considering the above data for each cell along with its neighbouring cells, correlated analysis is done. From the analysis, machine learning models have been trained which are adaptive to new measured data by using it for continuous training. This would provide the suggestions for load balancing and cell splitting and/or merging.

IV. Conclusions

In this work, details on the management system enabled with analytics and machine learning capabilities to support proactive monitoring and automation in the management of 5G networks is described. The architecture of the system with its components and few use case implementation details are also described. Prediction of anomalous network behaviour and traffic load prediction which in turn can be used to provide suggestions for effective network resource utilization have been implemented.

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