



# Combining Network Data Analytics Function and Machine Learning for Abnormal Traffic Detection in Beyond 5G

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# Agenda

Introduction

What is NWDAF?

NWDAF design

NWDAF implementation

NWDAF use case

Demo

Conclusion (Q/A session)

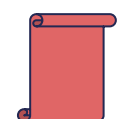
# Introduction

## → 5G Networks

- 5G is powered by use cases like ultra-fast broadband, mission-critical IoT, and low-latency services.
- Key components in 5G architecture include a Radio Access Network (RAN), and a Core Network (CN)
- Standardization for 5G is carried out by several international organizations, including: ITU, IEEE, 3GPP



Fig. 1. End-to-End Overview of 5G Networks Architecture [1].



[1] [https://software.org/wp-content/uploads/softwareorg\\_5Gsoftware.pdf](https://software.org/wp-content/uploads/softwareorg_5Gsoftware.pdf)

# Introduction

→ 5G Service Based Architecture (SBA)

- 3GPP Introduced the 5G Core Network Architecture as SBA [TS 23.501].
- Communication is realized through REST API calls using the HTTP routing mechanism over TCP.
- Several NFs are defined : SMF, AMF, UDR, ..., **NWDAF**.

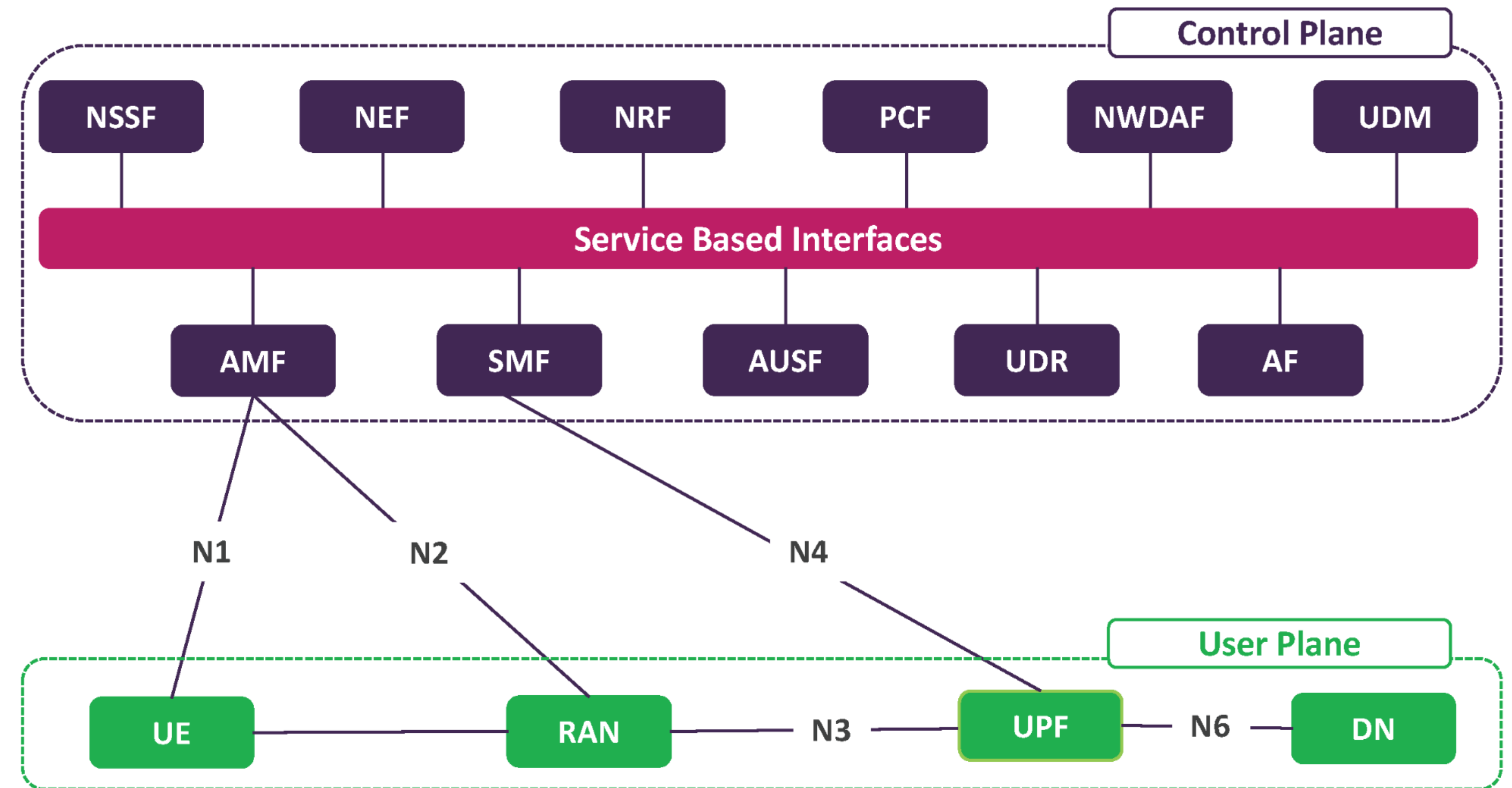
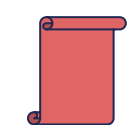


Fig. 2. 5G Service Based Architecture [2].



[2] Malik, S., Khan, M. A., El-Sayed, H., Khan, J., & Ullah, O. (2022). Implanting Intelligence in 5G Mobile Networks—A Practical Approach. *Electronics*, 11(23), 3933.

# What is NWDAF ?

**NWDAF** was defined to provide analytics to 5G NFs and OAM.

NWDAF provides two main services [3]:

- The NBI Analytics Info module allows clients to request and receive specific types of analytics information
- The NBI Events Subscription module enables clients to subscribe to or unsubscribe from various analytics events.

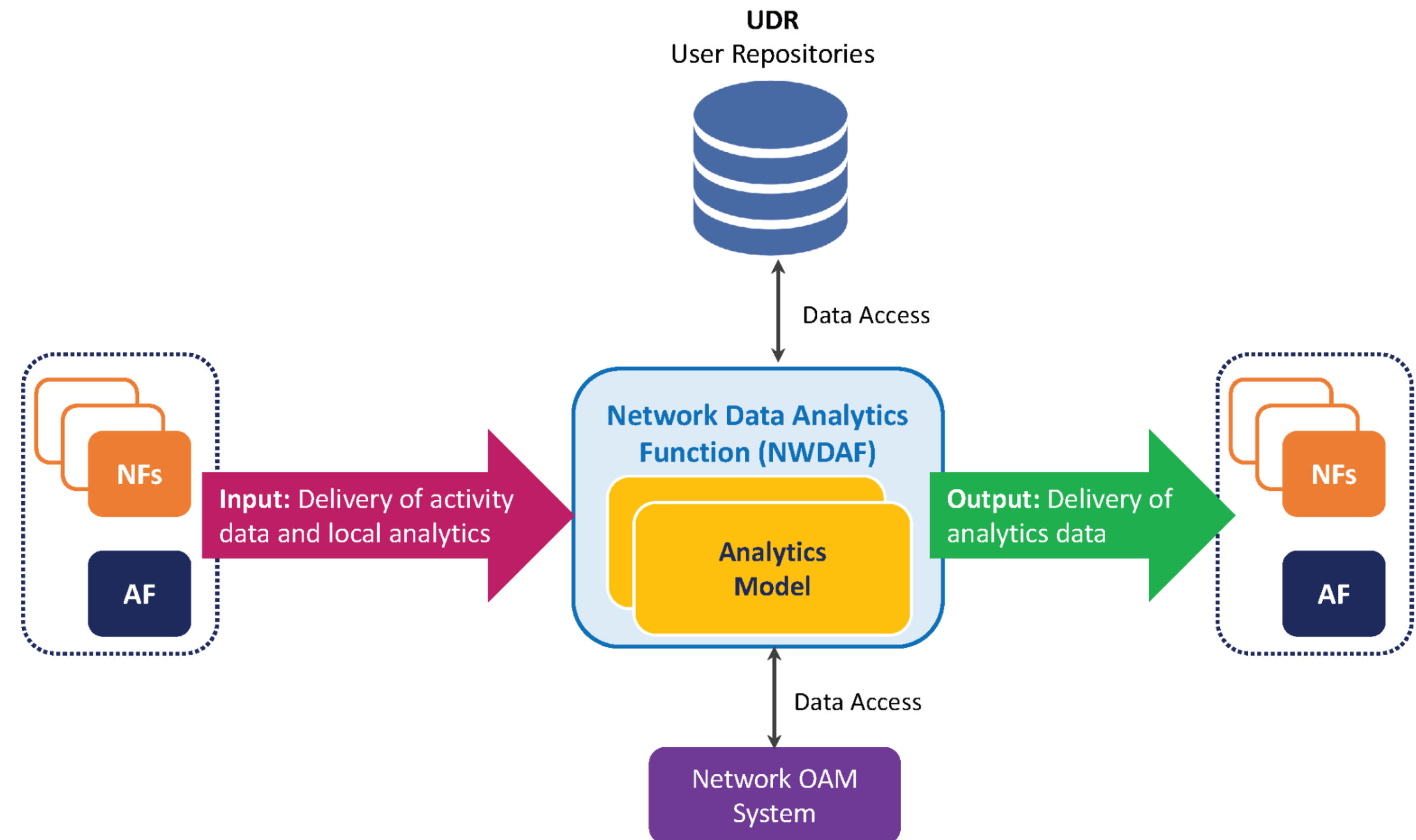


Fig. 3. Network Data Analytics Function [2].

[2] Malik, S., Khan, M. A., El-Sayed, H., Khan, J., & Ullah, O. (2022). Implanting Intelligence in 5G Mobile Networks—A Practical Approach. Electronics, 11(23), 3933.

[3] 3GPP. Technical Specification Group Core Network and Terminals; 5G System; Network Data Analytics Services; tech. rep. 29.520. Version 17.10.0. 2023

# NWDAF design

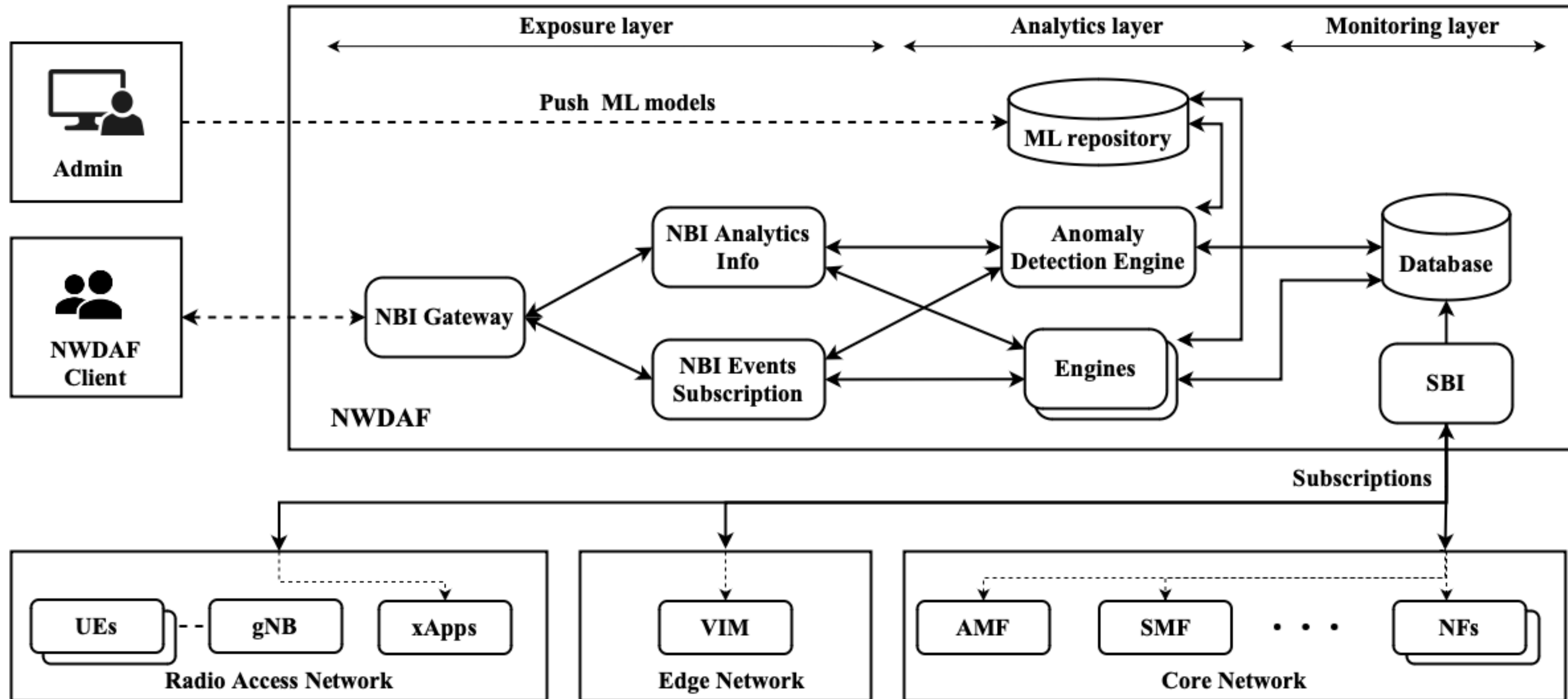


Fig. 4. Microservices-based NWDAF architecture.

# NWDAF implementation

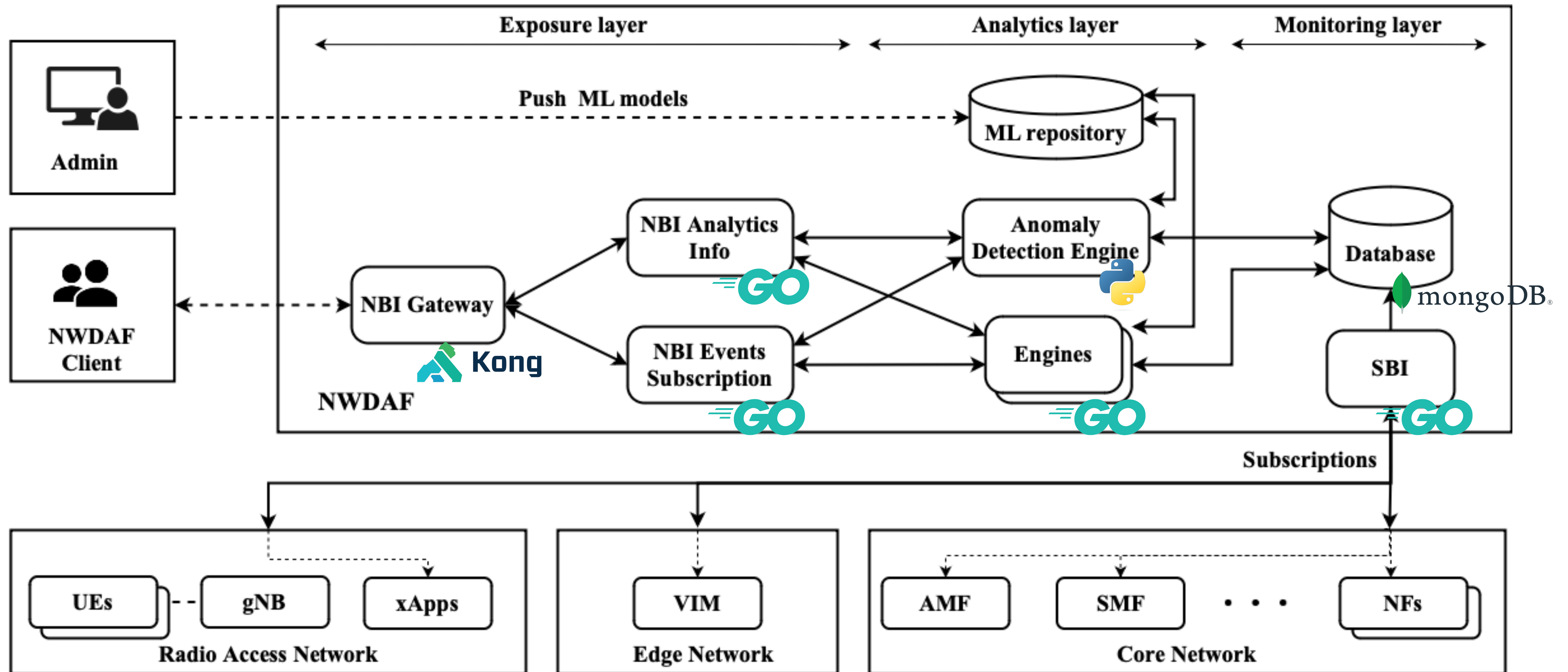


Fig. 4. Microservices-based NWDAF architecture.

# NWDAF use cases

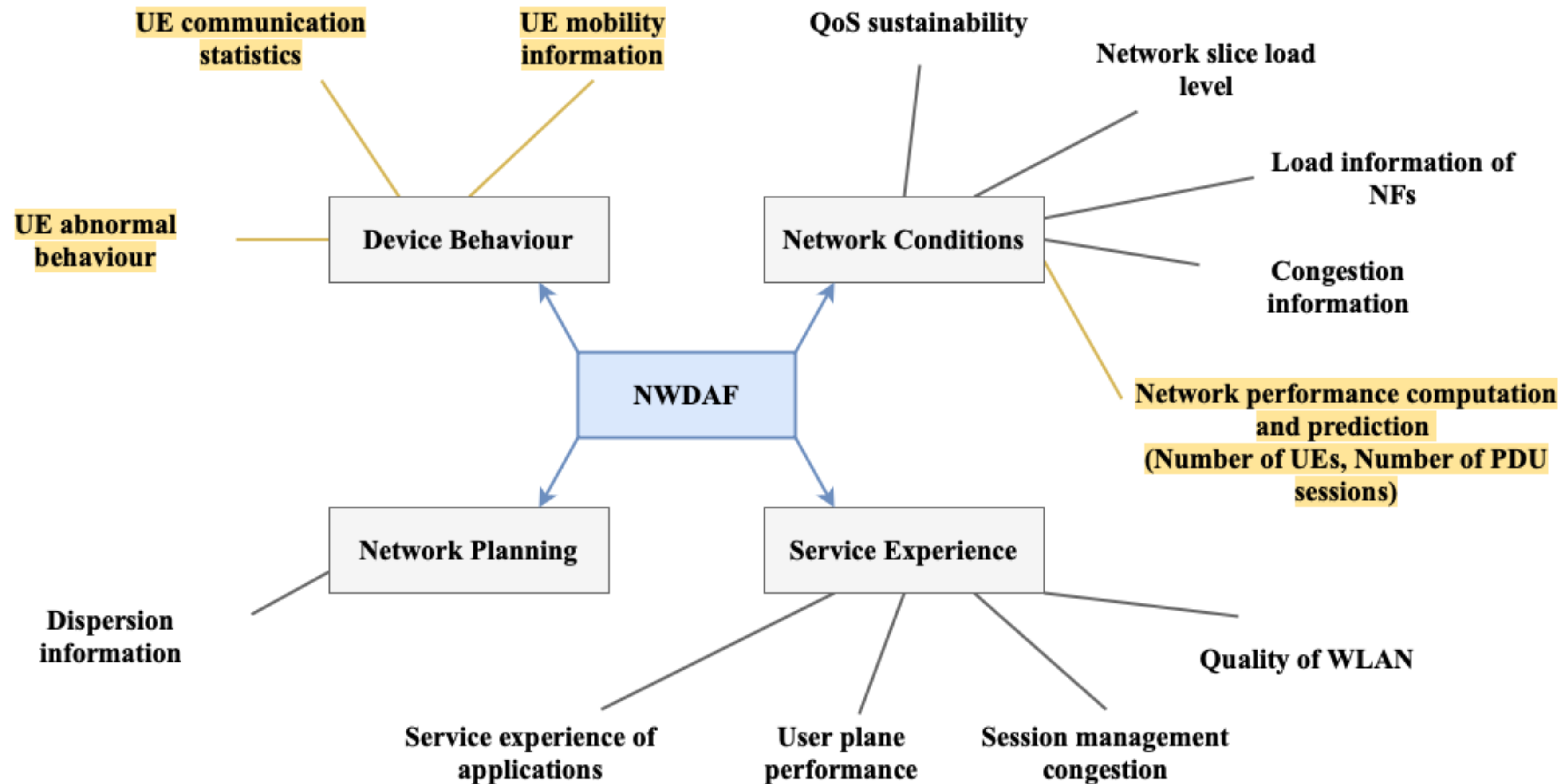
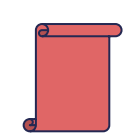


Fig. 5. A classification of 3GPP defined NWDAF Events[3].



[3] 3GPP. Technical Specification Group Core Network and Terminals; 5G System; Network Data Analytics Services; tech. rep. 29.520. Version 17.10.0. 2023

# NWDAF use cases

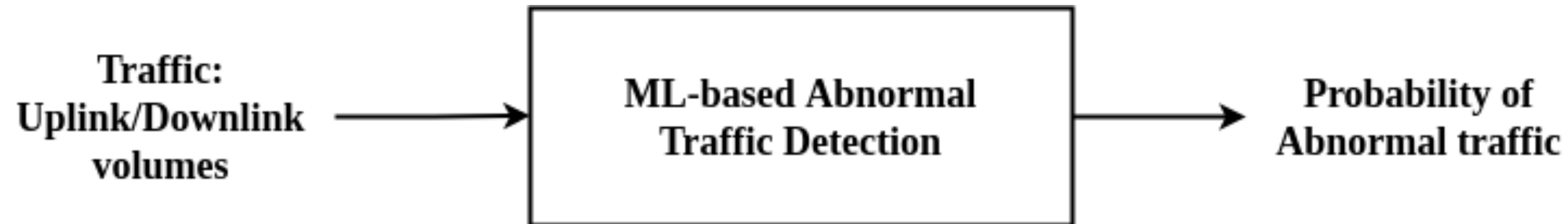
→ Core services

- The NWDAF provides support for two types of network performance events:
  - “num\_of\_ue”, measures the number of attach requests during a time window.
  - “sess\_succ\_rate”, measures the session success rate during a time window specified in the request.
- UE Communications: “ue\_comm” refer to the number of packets and bytes exchanged in the uplink and downlink directions for each PDU session.
- UE Mobility: "ue\_mobility" refers to the cell ID of a given UE.

# NWDAF use cases

→ ML-based services

- Abnormal Traffic: the NWDAF clients can subscribe to the "abnormal\_behaviour" event and exception ID "unexpected\_large\_rate\_flow" to receive periodic updates on the probability of abnormal traffic.



*Fig. 6. ML-based Abnormal Traffic Detection model.*

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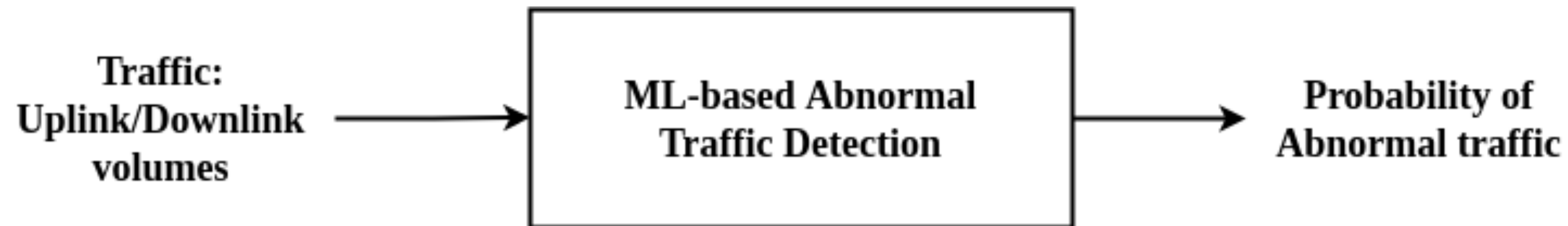


Fig. 6. ML-based Abnormal Traffic Detection model.

- Data pattern differs from UE to other → no generalization on data pattern → **no labeled dataset.**
- The ML-model will learn only the normal Uplink/Downlink pattern from historical data → It then will detect abnormal traffic → **AutoEncoder Architecture.**

# NWDAF use cases

→ ML-based services

- Encoding:  $X$  is compressed into a lower-dimensional space  $Z = \sigma(WX + b)$
- Decoding: decode  $Z$  to  $X'$  that is similar to the input dimension  $X' = \sigma'(W'Z + b')$

- The loss function is 
$$\text{MAE} = \frac{\sum_{i=1}^n |x'_i - x_i|}{n} = \frac{\sum_{i=1}^n |e_i|}{n}$$

- The traffic anomaly probability is

$$p = \min(\alpha \times |\beta' - \beta|, 1)$$

- $\alpha$  controls the impact of the distances scale.
- $\beta$  is the average train MAE.
- $\beta'$  is the test MAE.

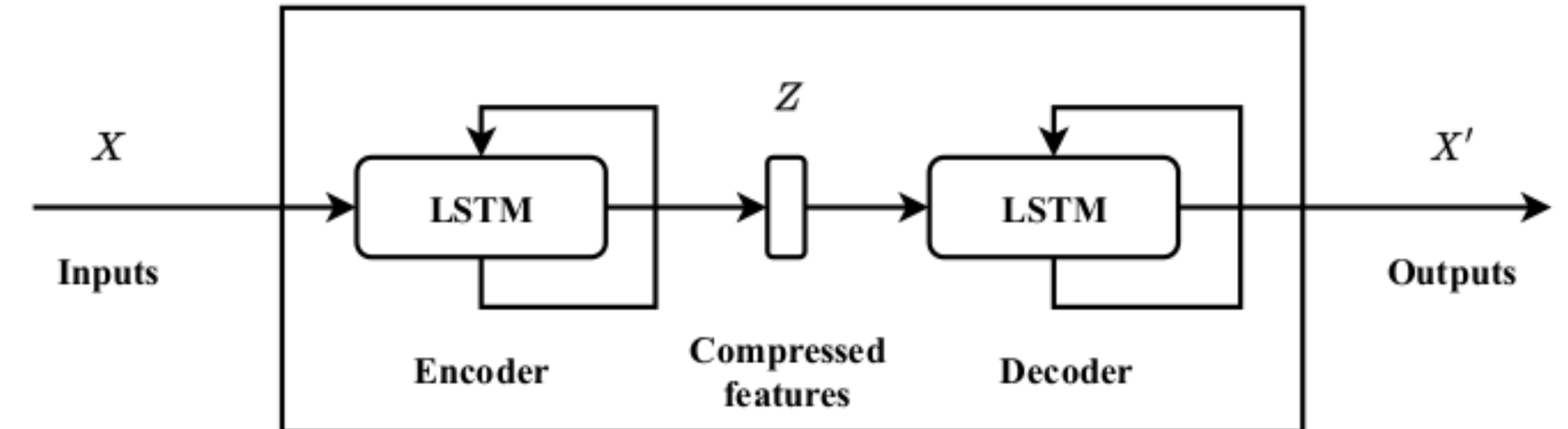
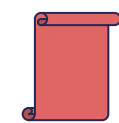


Fig. 7. LSTM Autoencoder architecture.

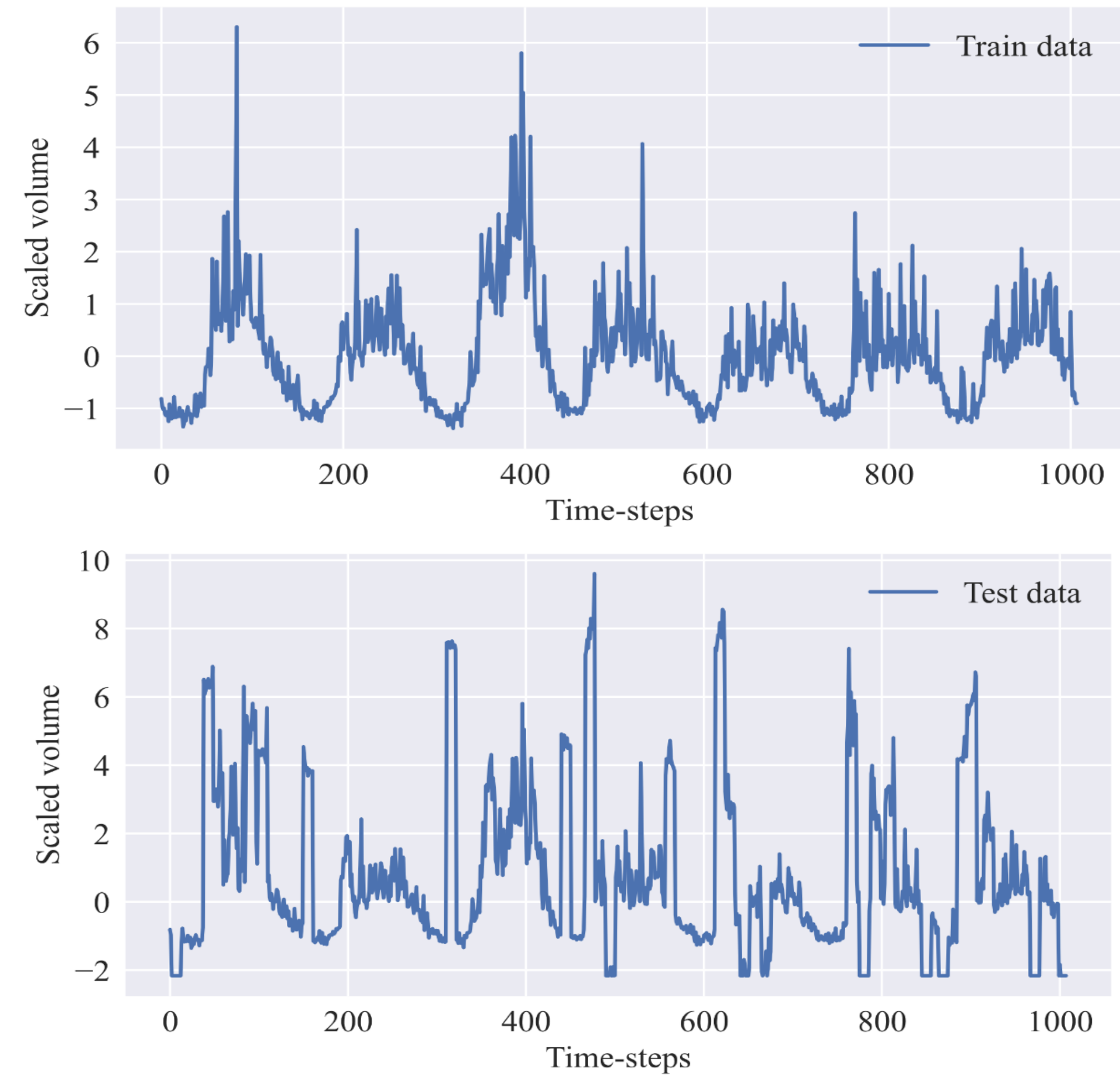
# NWDAF use cases

→ ML-based services

- We trained LSTM-based AE using Milano Dataset [5].
- We injected some anomalies in the pattern by introducing long traffic flows.



[4] Barlacchi, G., De Nadai, M., Larcher, R., Casella, A., Chitic, C., Torrisi, G., ... & Lepri, B. (2015). A multi-source dataset of urban life in the city of Milan and the Province of Trentino. *Scientific data*, 2(1), 1-15.



*Fig. 8. Train and Test data.*

# NWDAF use cases

→ ML-based services

- The distance between input and generated data correlates with the anomaly probability.
- The probabilities increase as the generated data diverges from the input data.
- The anomaly probability threshold is set to 0.5

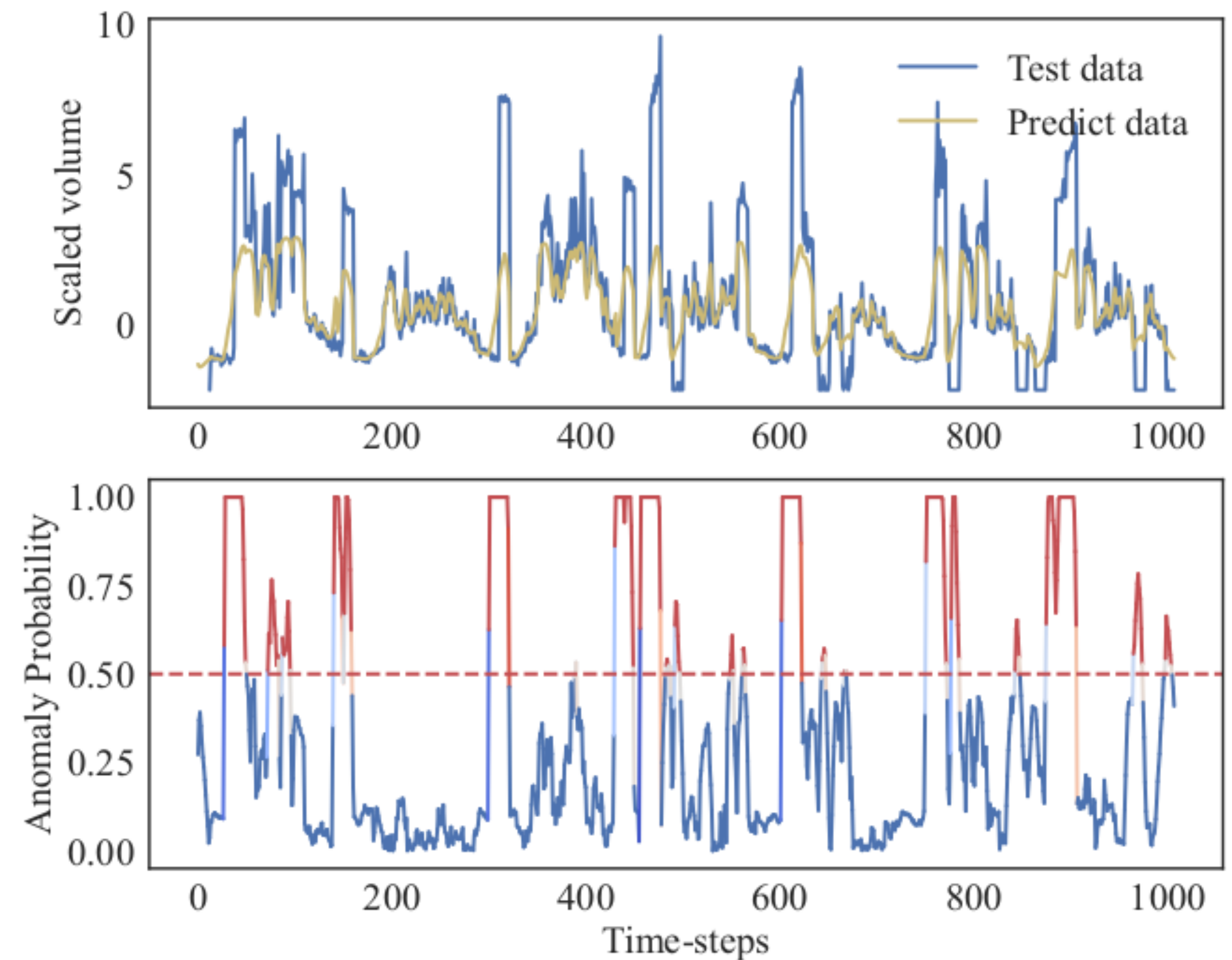
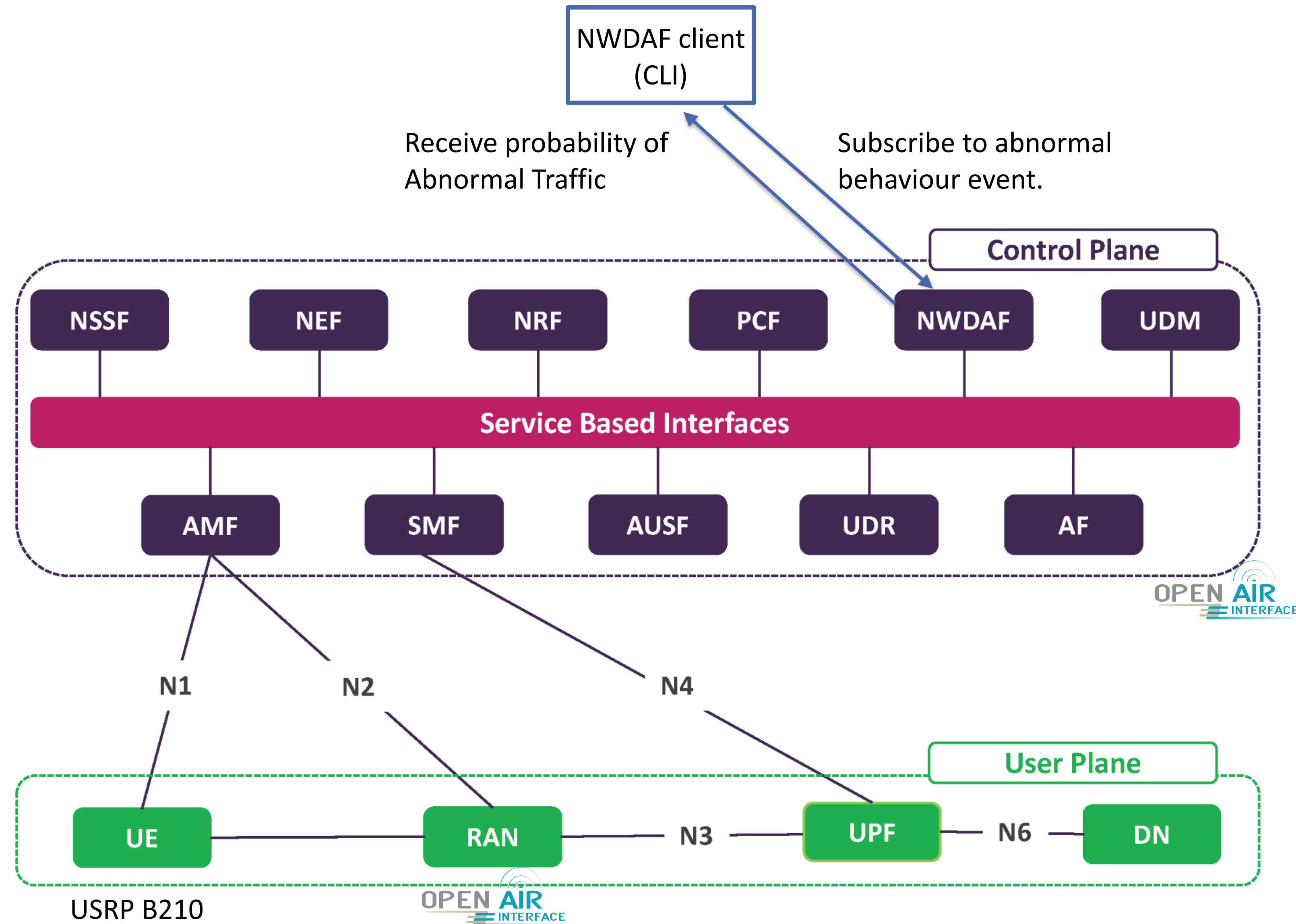


Fig. 11. Traffic anomaly probabilities for one week.

# DEMO



**DEMO**

**Thank you for your attention !**

**Q/A**