

NWDAF Implementation: Addressing Ping-Pong Issues in 5G Networks for Abnormal Behaviour Analytics

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Abstract—The complexity of 5G networks demands sophisticated automated monitoring systems, with artificial intelligence transforming network management through data-driven insights. The 3GPP-standardized Network Data Analytics Function (NWDAF) enables this automation by collecting and analyzing network data to optimize performance. This study employs NWDAF's abnormal behavior analysis to address ping-pong phenomena—excessive handovers between cells that degrade service quality through increased network load and latency. We propose a machine learning-driven handover management framework that proactively identifies potential ping-pong events before occurrence. Applied to real-world subscriber data from Viettel's core network, our approach demonstrates substantial reduction in ping-pong occurrences while preserving seamless connectivity. These findings offer practical insights for optimizing handover processes in high-density 5G deployments, directly improving user experience and network efficiency.

Keywords—ping-pong, 3GPP, NWDAF, abnormal behavior, XGBoost, 5G core network, handover.

I. INTRODUCTION

The evolution of mobile networks to 5G represents a significant leap in telecommunications technology, promising enhanced connectivity, ultra-low latency, and massive device support. The complexity of 5G networks, with their multi-layer architecture and diverse use cases, introduces new challenges in mobility management [1]. Traditional handover mechanisms from 4G networks face limitations in meeting the stringent requirements of 5G applications, particularly in scenarios demanding ultra-reliable low-latency communication (URLLC) [2]. While dense network deployments enhance coverage and capacity, they introduce complex mobility management challenges due to increased handover frequency. These scenarios require sophisticated optimization to manage signaling overhead, minimize ping-pong effects between neighboring cells, and maintain seamless connectivity during rapid cell transitions.

To address these challenges, The 3rd Generation Partnership Project introduce the Network Data Analytics Function (NWDAF) [3], a revolutionary network function that marks a significant departure from traditional 4G approaches. NWDAF serves as the analytics powerhouse of the 5G core

network, leveraging machine learning and artificial intelligence to provide data-driven insights for network optimization [2]. Unlike 4G networks, which largely relied on reactive and static optimization strategies, NWDAF enables predictive and adaptive network management by collecting and analyzing data from various network functions. This capability is particularly valuable in addressing historical 4G challenges such as congestion management, resource allocation, and mobility optimization.

Handover management remains a critical challenge in 5G networks, particularly in dense urban deployments where the ping-pong effect significantly degrades network performance and user experience. While traditional approaches rely on static thresholds and reactive mechanisms [4], the dynamic nature of 5G networks demands intelligent, predictive solutions. This paper leverages NWDAF's analytical capabilities and machine learning to not only detect but also predict ping-pong occurrences, enabling proactive handover management that reduces network load and improves service continuity in Viettel's operational network.

The main contributions of this work are summarized as follows:

- We design a modified handover procedure that integrates predictive analytics, allowing the the Access and Mobility Management Function (AMF) to make proactive decisions based on ping-pong likelihood.
- We construct a comprehensive dataset from real-world mobility patterns in Viettel's network, incorporating temporal and spatial features essential for accurate ping-pong prediction.
- We develop and validate an XGBoost-based model achieving 96.85% F1-score, demonstrating the feasibility of real-time ping-pong prediction in operational 5G networks.

The remainder of this paper is organized as follows: Section II reviews the fundamental concepts and related literature; Section III details the proposed methodology; Section IV presents the experimental results and analysis; finally, Section V concludes the paper.

II. BACKGROUND

Viettel's 5G network architecture is deployed in accordance with the 3GPP Release 16 specifications, including standardized handover procedures. However, the current implementation still exhibits instability, particularly during handover events, as it mainly emphasizes standard compliance rather than incorporating targeted optimization strategies at the core network level. Therefore, we have conducted a survey of existing methods to identify and develop a more suitable solution tailored to our system.

A. Handover Process

In mobile telecommunications, handover is a fundamental mechanism ensuring uninterrupted connectivity as User Equipment (UE) moves across diverse coverage areas. Within 5G networks, the 3GPP specifications categorize handover strategies based on interface usage [5], including the Xn-based inter NG-RAN approach, which relies on direct connections between gNBs, and the N2-based method, used when Xn interfaces are not available. This critical process involves the automated transfer of ongoing connections between radio channels, whether within a single cell (intra-cell handover) or across distinct cells (inter-cell handover), thus maintaining service continuity and Quality of Service (QoS) parameters.

Contemporary research on handover optimization has diverged into two primary directions. Traditional rule-based approaches, such as those by Hatipoglu et al. [6] and Kazi et al. [7], rely on signal strength metrics and predefined base station timing configurations to determine handover triggers. These methods involve calculating key configuration parameters, including handover trigger timing. However, in dynamic network environments, such static configurations are difficult to adapt promptly, leading to scalability limitations and suboptimal performance.

In contrast, predictive approaches attempt to enhance decision-making by forecasting user mobility and selecting the most appropriate target cell. For example, Farooq et al. [8] proposed a Semi-Markov mobility model capable of achieving 90% accuracy in next-cell prediction, while B. Cheikh et al. [9] developed an enhanced algorithm to optimize Femtocell Access Point selection based on user trajectory and contextual data. Despite their strengths, these models often struggle with prediction inaccuracies at the granularity of individual cells and do not fully resolve the inherent challenges of ping-pong handovers and dynamic handover regions.

While the above-mentioned approaches employ different strategies for optimizing or controlling the handover process, they are often constrained by limited adaptability and insufficient utilization of large-scale data. In our study, which focuses on the ping-pong handover problem, the vast amount of data, coupled with the spatial heterogeneity and uneven UE distribution, renders manual or static optimization methods inefficient. Consequently, we emphasize the need for automated and data-driven solutions with high precision, and thus, we turn our attention to machine learning-based approaches.

Machine learning offers a promising avenue for automating network operations and improving handover decisions. Within 5G networks, ongoing research has aimed to enhance overall efficiency through data-driven techniques [10], [11]. Alkhateeb et al. [12] employed LSTM networks to predict the base station a UE is most likely to connect to, using line-of-sight link information. While this method attempts to avoid congestion by anticipating future UE positions, it primarily addresses traffic redirection and does not tackle core issues like the ping-pong effect, which can cause significant localized instability.

Broader surveys on machine learning in mobility management have been presented in [13], summarizing various techniques primarily focused on the RAN layer, where decisions rely on radio-level metrics. In contrast, our work explores the potential of leveraging core network data to inform and optimize handover operations from a higher-layer perspective.

Although existing studies on machine learning demonstrate considerable potential, they often lack alignment with the specific challenges faced in the core network domain. Nevertheless, they offer valuable insights and a foundation upon which we can build more targeted solutions tailored to core-layer optimization, especially in the context of real-world deployments such as those within Viettel's infrastructure.

B. Ping-pong Issues

Ping-pong handover represents a significant challenge in mobility management, characterized by User Equipment (UE) undergoing frequent and unnecessary handovers between neighboring cells due to fluctuating signal strengths or suboptimal handover parameters. This oscillatory behavior introduces several detrimental effects: substantial increases in signaling overhead between UE, gNode-B (gNB), and core network elements saturate network resources and lead to control plane congestion, while the computational burden strains both UE and network infrastructure processing capabilities, resulting in resource exhaustion and timing synchronization issues [14], [15]. The frequent interruptions particularly impact real-time applications such as Voice over New Radio (VoNR) and Ultra-Reliable Low-Latency Communication (URLLC) services, leading to call drops and increased latency. Additionally, the heightened power consumption depletes UE battery life, ultimately compromising service availability across broader geographical areas and multiple user segments, as demonstrated by S. Park et al. in [16].

To address these challenges, recent studies have proposed various techniques aimed at reducing the ping-pong rate, primarily focusing on optimizing handover decisions in the Radio Access Network (RAN). For instance, D. Zidic et al. [17] introduced a novel metric based on station coverage and UE mobility patterns to better evaluate and predict ping-pong traffic, building upon earlier foundational work in [18]. Furthermore, [19] employed fuzzy logic to dynamically adjust handover configuration parameters, thereby reducing unnecessary handovers and improving decision granularity at the RAN level.

While the aforementioned approaches offer valuable insights into handover control within the RAN, they fall short in addressing core-layer dynamics. In contrast, our work investigates ping-pong behavior from a core network perspective, leveraging centralized data analytics to enable scalable and autonomous decision-making beyond traditional radio-based interventions. We will utilize the following formulas to evaluate the performance of the handover process:

- Failure Handover rate metric:

$$HPI = \frac{No. failure HO}{No. failure HO + No. success HO} \quad (1)$$

- Ping-pong Handover rate metric:

$$PPR = \frac{No. PingPong}{No. failure HO + No. success HO} \quad (2)$$

C. UE Movement Information

Our data set consists of system log files that record network events, including handover processes along with their associated outcomes (e.g. success or failure). Each event is accompanied by information about the User Equipment (UE) and the target cell where the UE attempts to perform the handover. The information extracted from the log files, which is used for our study, is illustrated in Table I.

TABLE I: Information form log files

field name	Description	Sample value
Timestamp	epoch time	1729499399407
IMSI	subscriber identification	45204**09
EventID	event identification	handover
Result	event result	success
CellID	cell identification	23**58

Our collected data encompasses log information from multiple geographical regions, each characterized by distinct network behavioral patterns. Urban areas typically exhibit high device density and frequent handover activities, while rural regions such as mountainous areas demonstrate significantly lower access patterns, and suburban zones often present moderate levels of network utilization. This geographical diversity in network conditions necessitates region-specific processing approaches for effective anomaly detection and handover optimization. Several prior studies have addressed this challenge by proposing area-specific labeling methodologies to facilitate targeted processing [17], [20]. However, manual pre-labeling approaches present substantial limitations in scalability and resource requirements, demanding extensive human expertise for accurate classification. Furthermore, such approaches lack feasibility for large-scale deployment. To address these limitations, we propose an automated regional segmentation approach that eliminates manual labeling while maintaining processing effectiveness across diverse geographical contexts. The detailed methodology for this automated segmentation will be elaborated in Sec. III.

III. PROPOSED SOLUTION

To address the ping-pong challenge in Viettel's 5G network, we develop a comprehensive analytics framework that transforms raw mobility historical data into actionable insights. An overview of our approach is visualized in Figure 1, which illustrates two complementary operational modes: detection and prediction. The detection mechanism (Section III-A) serves dual purposes: generating labeled training data for the prediction model by identifying historical ping-pong patterns, and providing real-time monitoring metrics for network performance evaluation. The prediction component (Section III-B) takes a fundamentally different approach by analyzing handover requests before they are executed.

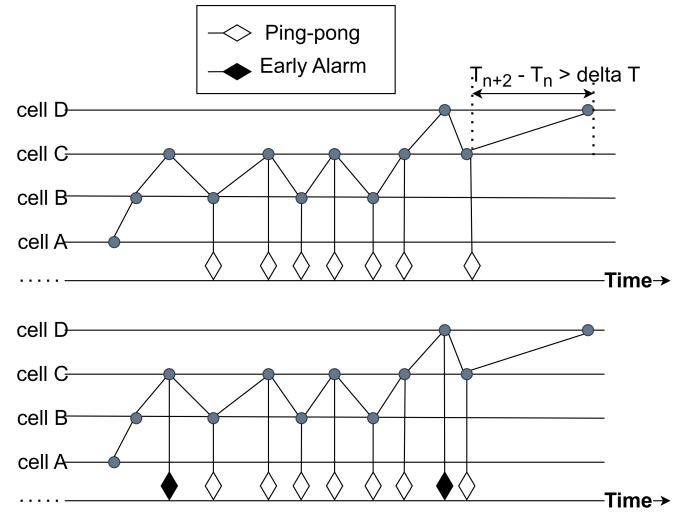


Fig. 1: Ping-pong detection (top) and prediction (bottom) process

A. Ping-Pong Detection

In mobile networks, detecting ping-pong handovers—rapid, successive transitions between adjacent cells where a user equipment (UE) alternates between the same set of cells—is essential for identifying potential network instability and mobility management inefficiencies (see Fig. 1).

The detection algorithm monitors the sequence of handover events over time, analyzing both their temporal proximity and spatial transition patterns. A ping-pong condition is flagged when two criteria are simultaneously met: (1) the time interval between alternating handovers falls below a predefined threshold ($T_{i+1} - T_i \leq \Delta T$), and (2) the UE returns to a previously visited cell within the observation window, such as $Cell_{i+2} = Cell_i$ [18]. The detailed implementation of this detection process is presented in Algorithm 1.

Algorithm 1 Ping-pong Handover Detection (Overall Count)**Input :** (*timestamp, source, target*)**Output:** Total number of ping-pong handovers

```

1 Initialization
2    $\lfloor \text{PingPongCount} \leftarrow 0$ 
3 foreach  $UE \in \text{Network}$  do
4   foreach consecutive handover triple  $(h_n, h_{n+1}, h_{n+2}) \in \text{HandoverHistory}$  do
5     if  $(\text{cell}_n \neq \text{cell}_{n+1}) \wedge (\text{cell}_n = \text{cell}_{n+2}) \wedge (T_{n+2} - T_n \leq \Delta T)$  then
6        $\lfloor \text{PingPongCount} \leftarrow \text{PingPongCount} + 1$ 
7 return  $\text{PingPongCount}$ 

```

B. Ping-Pong Prediction

The prediction module aims to prevent ping-pong issues by analyzing handover requests in real-time. Unlike detection, which identifies ping-pong after it occurs, prediction uses the UE's recent movement history to determine the likelihood of such ping-pong behavior. When a high probability of a ping-pong event is predicted, AMF — the 5G core network element responsible for mobility management — rejects the handover request, thereby avoiding unnecessary signaling overhead and potential service disruption. This predictive intervention enables the AMF to make intelligent decisions at the critical moment when a UE requests handover to a target cell. For example, if a UE at cell B requests handover to cell C, the model evaluates whether this movement is likely to result in a rapid return to cell B based on historical patterns and current network state, allowing the AMF to approve or deny the request accordingly.

Differences in population density across geographic areas result in uneven distributions of UEs within the network, which in turn give rise to region-specific behavioral patterns. Capturing these patterns is crucial for enhancing model performance, motivating the inclusion of region-level clustering as an input feature. Therefore, we divide the cells into distinct groups based on their UE density, using the K -means clustering algorithm [21]. The advantage of K -means is that it does not require labeled data; instead, it only needs information such as the number of UEs accessing the network and the number of procedures over time as input. K -means utilizes a formula to calculate the distance between cells:

$$d(x_i, c_j) = \sqrt{\sum_{k=1}^n (x_{ik} - c_{jk})^2}, \quad (3)$$

where $d(x_i, c_j)$ is the distance between cell data x_i and centroid c_j ; where $x_i = [n_{UE}^{(i)}, n_{events}^{(i)} \in \mathbb{R}^{2T}]$ denotes the concatenated feature vector aggregating UE count statistics and event frequency metrics for the i -th cell across the temporal dimension; x_{ik}, c_{jk} is the value of the k -th element of x_i and c_j ; T denotes the number of time steps.

Using the historical mobility data of the UEs, we construct a dataset to serve as input for the prediction model. Specifically,

each time a UE sends a handover request to the network core, a data sample is generated in the following format:

- $t_previous_ue_ho$: time interval to the most recent previous handover of the UE,
- $t_previous_ue_pp$: time interval to the most recent previous ping-pong of the UE,
- is_ue_pp : is *True* if UE has experienced ping-pong, and *False* otherwise,
- $is_ue_pp_15m$: is *True* if UE has experienced ping-pong within the past 15 minutes, and *False* otherwise,
- $is_ue_cell_pp$: is *True* if UE has previously experienced ping-pong within that cell, and *False* otherwise,
- is_cell_pp : is *True* if cell has experienced ping-pong, and *False* otherwise,
- $is_cell_pp_15m$: is *True* if cell has experienced ping-pong within the past 15 minutes, and *False* otherwise,
- is_now_pp : is *True* if handover is a ping-pong event, and *False* otherwise,
- $cluster_id$: cluster identification of cells,
- $previous_ue_ho_result$: ue's handover result this time,
- $now_ue_ho_result$: ue's handover result last time,
- $label_t$: is *True* if $cell_{t+1} \equiv cell_{t-1}$, and *False* otherwise.

Using the "label_t" feature as the target labels, we train classification models on the generated dataset. In this context, the terms "prediction" and "classification" are used interchangeably.. This is because the data at timestamp t is constructed using past information (t^-), while label creation relies on future information (t^+).

We employ Extreme Gradient Boosting (XGBoost) [22] due to its proven effectiveness with tabular data and ability to handle imbalanced datasets. XGBoost is an optimized implementation of gradient-boosted decision trees that offers superior performance through regularization, parallel processing, and efficient handling of missing values - all critical for our real-time network environment where data completeness cannot be guaranteed. The key features of XGBoost align well with the solution we are seeking:

- 1) Gradient Boosting Framework: XGBoost employs a gradient boosting approach, where decision trees are sequentially added to the model to correct errors made by previous trees. Optimize a differentiable loss function using second-order gradient information, leading to faster convergence.
- 2) Regularization: XGBoost incorporates both L_1 (Lasso) and L_2 (Ridge) regularization to prevent overfitting, making it particularly effective in handling complex datasets with high dimensionality.
- 3) Feature Importance: XGBoost provides robust tools to measure feature importance, allowing for interpretability of the model and insights into the underlying data.
- 4) Parallelization: Unlike traditional gradient boosting implementations, XGBoost supports parallelized tree construction, significantly improving computational efficiency.

The objective function of XGBoost is defined as:

$$\mathcal{L} = \sum_{i=1}^n \ell(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k), \quad (4)$$

where:

- $\ell(y_i, \hat{y}_i)$ is the loss function that measures the difference between predicted ($\hat{y}_i$) and actual (y_i) values.
- $\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \|w\|^2$ is the regularization term, where:
 - T : Number of leaf nodes.
 - w : Leaf weight vector.
 - γ and λ : Regularization parameters.

XGBoost is particularly known for its ability to handle large datasets, robustness to overfitting, and flexibility in model tuning. We expect XGBoost to have strong capabilities for learning from tabular data and to be the most optimal solution for our needs.

We propose several suggestions to enhance the efficiency of the handover process. Specifically, if "label_t" is predicted to be True, suggesting an imminent ping-pong handover, the handover process will be proactively canceled. In this case, the user will continue using the service within the current cell. This recommendation aims to alleviate the load on the core network by eliminating the need for processing communication flows associated with the handover procedure in such scenarios.

IV. EXPERIMENTAL RESULTS

A. Experimental Setup

Our experimental data was collected on October 21st, within the time frame of 14:00 to 18:00. The specific details are described as follows:

- Number of UEs: 120000
- Number of cell: 6000
- Number of cluster of K -means: 3
- ΔT : 1 second

B. Discussion

After applying the K -means algorithm, cells were partitioned into three distinct clusters. Fig. 3 visualizes the model results based on the number of UEs within each cell and the number of handover events occurring in the cell. Cluster 0 contains low-traffic cells, Cluster 1 comprises high-traffic cells, and Cluster 2 represents medium-traffic cells.

We analyzed handover volume, Handover Failure Rate (HPI), and Ping-Pong Rate (PPR) for each cluster using 15-minute time windows. The handover graph illustrates the results across three clusters. From the visual results, it is evident that HPI and PPR do not directly correlate with the number of handovers. The observed increase in handovers during periods of higher user mobility, such as around 17:00, is a typical phenomenon and should not be interpreted as a root cause of failure. Meanwhile, HPI and PPR show a high correlation, underscoring the impact of ping-pong events on handover failures. Furthermore, the data among clusters

reveal a degree of locality, as they do not exhibit consistent fluctuations across different time frames.

The evaluation metrics for the prediction process include accuracy, precision, recall, and F1-score. The methods compared to select the most suitable solution are Decision Tree (DT), Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), and Deep Neural Networks (DNN).

Label *True* (early alarm) accounts for only 1.34% of the total samples, the training process is rendered ineffective. To address imbalanced nature of the dataset, we applied the concept of K -fold Cross-Validation.

Specifically, the label *False* data was divided into several smaller subsets. In each training iteration, the model was trained using one subset of label *False* data combined with the entire label *True* in training dataset until all subsets were utilized. The test set also suffers from an imbalance, with the label *True* comprising approximately 1.35% of the samples. As a result, the F1-score serves as the primary metric for evaluation.

TABLE II: The results of the classification process.

Model	Accuracy	Precision	Recall	F1-score
DT	95.99	95.37	96.19	95.78
SVM	89.34	88.91	91.02	89.95
LR	90.18	87.54	92.26	89.84
RF	95.91	95.11	96.13	95.62
DNN	94.52	95.25	92.11	93.65
XGB	97.09	95.64	98.10	96.85

As presented in Table II, tree-based classification models demonstrate superior performance (DT, RF, XGB), with XGB standing out as the best-performing model. It achieves significant optimization across all four evaluation metrics, particularly an impressive F1-score of 96.85%.

Based on XGBoost weight information, the importance values of the features are calculated to reflect the contribution of each feature to the prediction results. For our dataset, this parameter is illustrated in Fig. 5, where features such as "t_previous_ue_ho" and "cluster_id" demonstrate significant importance for the prediction. This serves as a basis for us to create additional features and eliminate less impactful ones. By doing so, we can optimize computational time and improve model performance.

V. CONCLUSION

In this study, we addressed the ping-pong issue to improve handover quality in 5G networks. By leveraging the historical mobility data of UEs, we constructed a dataset and applied XGBoost model for prediction. The model demonstrated its effectiveness, achieving an accuracy of 96.85% (F1-score). Resolving the ping-pong problem contributes to the deployment of NWDAF with highly practical features for Viettel's 5G network. However, further enhancements are necessary to prevent users from being unable to perform legitimate handovers and to ensure that detection speeds are sufficient to handle the large volume of UEs and data.

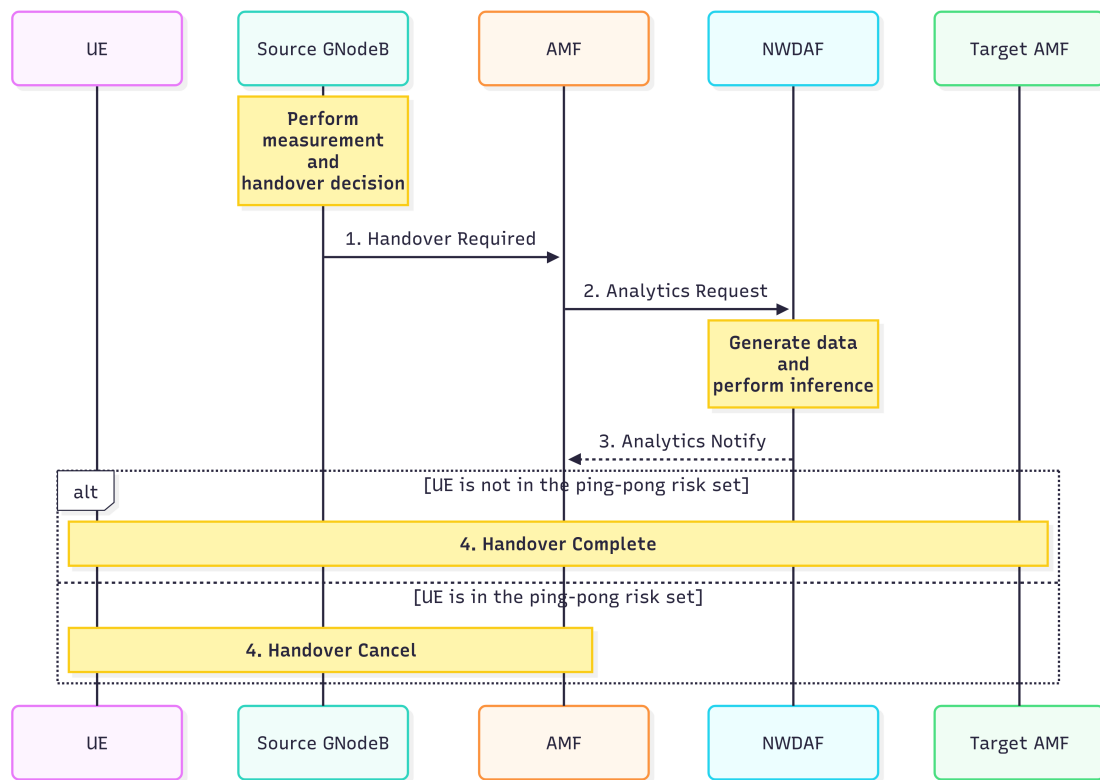


Fig. 2: NWDAF flow in 5G core

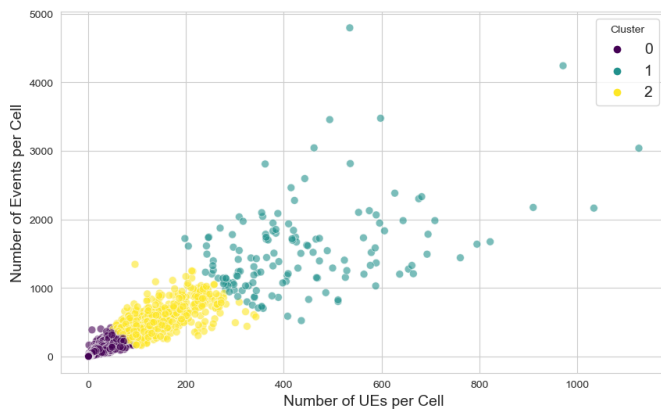


Fig. 3: Visualizing the clustering of cells

Our future work involves expanding experiments on larger datasets beyond the current 4-hour scope. This presents computational challenges, but offers the advantage of increased data diversity. Additionally, developing new models to further optimize the results is crucial.

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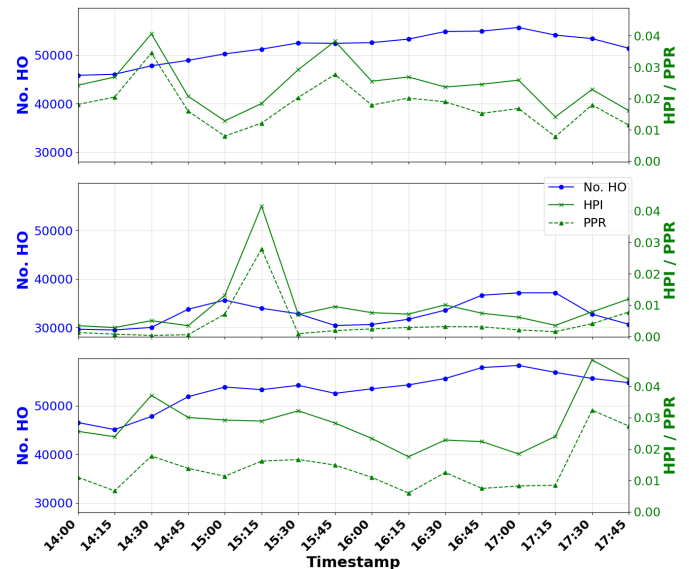


Fig. 4: Handover indicators at cluster 0, 1 and 2.

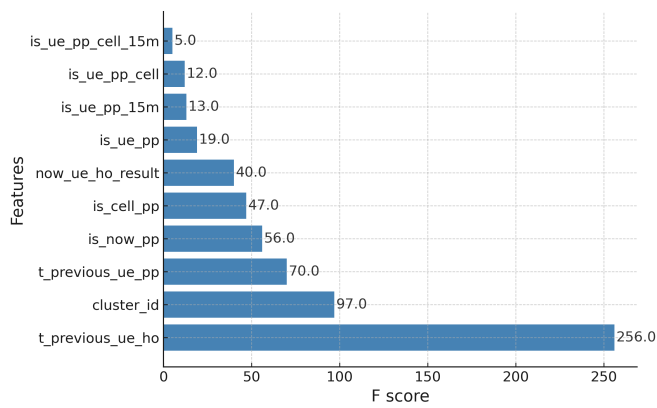


Fig. 5: Features Importance

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