# 4G ML Network Analysis Notebook

Prepared by: Onur Tuncay

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## Nobebook Structure

This notebook is organized to provide a step-by-step exploration of a 4G mobile network dataset, applying data science and machine learning methodologies across multiple tasks. The structure is aligned with the designated tasks and aims to ensure clarity and coherence throughout the analysis:

- Section 1 introduces the motivation and rationale for selecting the dataset, with a focus on its relevance and suitability for real-world network analysis.
- Section 2 offers an overview of the selected dataset, highlighting its features, structure, and variables that will be used throughout the analysis.
- Section 3 (Task 1) covers data preprocessing and exploration, including initial data summaries, handling of categorical and temporal columns, treatment of missing values, outlier detection, and data normalization. This section also presents various visualizations to uncover patterns within the dataset.
- Section 4 (Task 2) is dedicated to clustering analysis, where both K-Means and Agglomerative clustering techniques are applied. The performance of clustering algorithms is compared, and clusters are interpreted using domain-relevant variables.
- Section 5 (Task 3) addresses classification tasks, involving both binary and multi-class classification. Several models are trained and evaluated using metrics such as accuracy and F1-score, supported by feature importance and SHAP analysis for interpretability.
- Section 6 (Task 4) demonstrates the use of Genetic Algorithms for hyperparameter optimization, focusing on improving the performance of a Random Forest classifier through evolutionary computation principles.
- Section 7 provides references for this notebook.

This structure ensures a comprehensive analysis framework that integrates exploratory data analysis, unsupervised learning, supervised classification, and model optimization. It provides a data-driven perspective on mobile network behavior and supports data-informed decision-making for performance enhancement.

# 1. Dataset Selection

In [6]:
```
# Import essential libraries
import pandas as pd  # Data manipulation and analysis using DataFrames
import glob  # File handling and retrieval using patterns
import numpy as np  # Numerical computing, including arrays and mathematical operations
import seaborn as sns  # Statistical data visualization
import matplotlib.pyplot as plt  # Fundamental plotting library

# Import preprocessing utilities
from sklearn.preprocessing import StandardScaler  # Standardizing features (zero mean, unit variance)
from sklearn.preprocessing import LabelEncoder  # Encoding categorical variables into numerical format

# Import statistical functions
from scipy.stats import zscore  # Compute Z-score for outlier detection
from scipy.stats import chi2_contingency  # Perform Chi-square test for categorical independence

# 3D visualization tools
from mpl_toolkits.mplot3d import Axes3D  # Enables 3D plotting

# Clustering algorithms
from sklearn.cluster import KMeans  # K-Means clustering for unsupervised learning
from sklearn.metrics import silhouette_score  # Evaluate clustering quality with silhouette score
from sklearn.decomposition import PCA  # Dimensionality reduction via Principal Component Analysis
from sklearn.cluster import AgglomerativeClustering  # Hierarchical clustering

# Hierarchical clustering visualization
from scipy.cluster.hierarchy import dendrogram, linkage  # Create dendrograms for hierarchical clustering

# Explainability tools
import shap  # SHAP values for feature importance explanation in machine learning models

# Train-test split utility
from sklearn.model_selection import train_test_split  # Splits data into training and testing sets
from sklearn.model_selection import cross_val_score  # Cross-validation

# Classification models
from sklearn.ensemble import RandomForestClassifier  # Ensemble tree-based classifier
from sklearn.linear_model import LogisticRegression  # Logistic regression for binary classification

# Evaluation metrics
from sklearn.metrics import accuracy_score  # Compute classification accuracy
from sklearn.metrics import confusion_matrix  # Generate confusion matrix for model evaluation
from sklearn.metrics import classification_report  # Summarize precision, recall, F1-score
from sklearn.metrics import f1_score, precision_score, recall_score, make_scorer  # Individual classification metrics

import random  # Random number generation for parameter selection
import scipy.stats as stats  # Statistical functions like z-score


# Suppress warnings for readability
import warnings
warnings.filterwarnings("ignore")  # Ignore unnecessary warnings

# Configure Pandas display settings
pd.set_option('display.max_rows', 2000)  # Show up to 2000 rows in DataFrame outputs
pd.set_option('display.max_columns', 500)  # Show up to 500 columns in DataFrame outputs
```

In [7]:
```
pwd  #Check current directory
```

Out[7]:
```
'C:\\Users\\onurt\\OneDrive\\Desktop\\UoG Msc Data Science\\CT7205 - Machine Learning and Optimisation\\Assessment\\dataset'
```

In [8]:
```
# File path of the datasets
file_path = "C:\\Users\\onurt\\OneDrive\\Desktop\\UoG Msc Data Science\\CT7205 - Machine Learning and Optimisation\\Assessment\\dataset/*.csv"

# An empty dictionary to store DataFrames
dataframes = {}

# Loop through all CSV files
for file in glob.glob(file_path):
    # Extract the file name and use it as a key
    file_name = file.split("\\")[-1].split(".")[0]
    # Read the CSV file into a DataFrame and replace "?" values with NaN
    df = pd.read_csv(file, index_col=0, na_values="?")
    # Save the DataFrame in the dictionary
    dataframes[file_name] = df

    # File name
    print(f"File: {file_name}")
    # Shape and missing value analysis
    print(f"Shape: {df.shape}")
    print("Missing Values:\n", df.isnull().sum())
    print("\nPercentage of Missing Values:\n", (df.isnull().sum() / len(df) * 100).round(2))

    # General information about the DataFrame
    print("\n--- DataFrame Info ---")
    df.info()

    # Summary statistics of the DataFrame
    print("\n--- Summary Statistics ---")
    print(df.describe())

    print("\n" + "-" * 40 + "\n")
```

```
File: 4G - Passive measurements
Shape: (527540, 26)
Missing Values:
 Date                      0
Time                       0
UTC                    70339
Latitude                   0
Longitude                  0
Altitude               70339
Speed                  70339
EARFCN                     0
Frequency                  0
PCI                        0
MNC                        0
CellIdentity               0
eNodeB.ID                  0
Power                  21714
SINR                   21714
RSRP                       0
RSRQ                       0
scenario                   0
cellLongitude              0
cellLatitude               0
cellPosErrorLambda1     7908
cellPosErrorLambda2        0
n_CellIdentities           0
distance                   0
Band                       0
campaign                   0
dtype: int64

Percentage of Missing Values:
 Date                    0.00
Time                     0.00
UTC                     13.33
Latitude                 0.00
Longitude                0.00
Altitude                13.33
Speed                   13.33
EARFCN                   0.00
Frequency                0.00
PCI                      0.00
MNC                      0.00
CellIdentity             0.00
eNodeB.ID                0.00
Power                    4.12
SINR                     4.12
RSRP                     0.00
RSRQ                     0.00
scenario                 0.00
cellLongitude            0.00
cellLatitude             0.00
cellPosErrorLambda1      1.50
cellPosErrorLambda2      0.00
n_CellIdentities         0.00
distance                 0.00
Band                     0.00
campaign                 0.00
dtype: float64

--- DataFrame Info ---
<class 'pandas.core.frame.DataFrame'>
Index: 527540 entries, 231098 to 43631
Data columns (total 26 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   Date                 527540 non-null  object
 1   Time                 527540 non-null  object
 2   UTC                  457201 non-null  float64
 3   Latitude             527540 non-null  float64
 4   Longitude            527540 non-null  float64
 5   Altitude             457201 non-null  float64
 6   Speed                457201 non-null  float64
 7   EARFCN               527540 non-null  int64
 8   Frequency            527540 non-null  float64
 9   PCI                  527540 non-null  int64
 10  MNC                  527540 non-null  object
 11  CellIdentity         527540 non-null  int64
 12  eNodeB.ID            527540 non-null  int64
 13  Power                505826 non-null  float64
 14  SINR                 505826 non-null  float64
 15  RSRP                 527540 non-null  float64
 16  RSRQ                 527540 non-null  float64
 17  scenario             527540 non-null  object
 18  cellLongitude        527540 non-null  float64
 19  cellLatitude         527540 non-null  float64
 20  cellPosErrorLambda1  519632 non-null  float64
 21  cellPosErrorLambda2  527540 non-null  float64
 22  n_CellIdentities     527540 non-null  int64
 23  distance             527540 non-null  float64
 24  Band                 527540 non-null  int64
 25  campaign             527540 non-null  object
dtypes: float64(15), int64(6), object(5)
memory usage: 108.7+ MB

--- Summary Statistics ---
                UTC       Latitude      Longitude       Altitude  \
count  4.572010e+05  527540.000000  527540.000000  457201.000000
mean   1.611747e+09      41.883335      12.485928      69.469625
std    1.184731e+06       0.014385       0.022367      41.151498
min    1.610528e+09      41.823736      12.418497    -139.740000
25%    1.610724e+09      41.871599      12.464796      43.870000
50%    1.610978e+09      41.890723      12.494066      65.650000
75%    1.612688e+09      41.893862      12.495141      89.340000
max    1.614353e+09      41.903102      12.533860     416.550000

               Speed         EARFCN      Frequency            PCI  \
count  457201.000000  527540.000000  527540.000000  527540.000000
mean        5.523218    2874.847323    1852.404799     224.198226
std        10.055164    2101.187984     655.671952     143.373641
min         0.000000     501.000000     806.000000       1.000000
25%         0.720000    1225.000000    1807.500000     103.000000
50%         2.590000    1850.000000    1870.000000     198.000000
75%         4.790000    3175.000000    2647.500000     323.000000
max        79.270000    6400.000000    2662.500000     503.000000

       CellIdentity      eNodeB.ID          Power           SINR  \
count  5.275400e+05  527540.000000  505826.000000  505826.000000
mean   4.442894e+07  173550.426119     -75.152770       0.887128
std    2.921215e+07  114109.989590      14.170568      10.620611
min    1.691931e+07   66091.000000    -125.230000     -20.930000
25%    1.771958e+07   69217.000000     -84.710000      -8.500000
50%    1.776797e+07   69406.000000     -74.860000       2.820000
75%    7.684507e+07  300176.000000     -65.700000       7.300000
max    7.745152e+07  302545.000000     -22.400000      39.020000

                RSRP           RSRQ  cellLongitude   cellLatitude  \
count  527540.000000  527540.000000  527540.000000  527540.000000
mean      -99.071670     -20.398189      12.486287      41.883051
std        14.119162       5.396874       0.022390       0.015900
min      -145.520000     -49.890000      12.418621      41.824584
25%      -108.570000     -24.360000      12.467131      41.871271
50%       -99.100000     -19.550000      12.493153      41.890689
75%       -89.650000     -15.870000      12.497913      41.896503
max       -43.170000      -7.990000      12.543056      41.902997

       cellPosErrorLambda1  cellPosErrorLambda2  n_CellIdentities  \
count        519632.000000        527540.000000     527540.000000
mean             12.593485            12.335065          7.676123
std              13.495714            13.537118          2.966718
min               0.139538             0.000000          1.000000
25%               0.358485             0.246736          5.000000
50%              10.810001            10.810001          8.000000
75%              20.130005            20.130005         10.000000
max             100.000000           100.000000         13.000000

           distance           Band
count  527540.000000  527540.000000
mean      555.458030       7.667083
std       796.369764       7.085365
min         0.000000       1.000000
25%       158.577997       3.000000
50%       286.565321       3.000000
75%       616.922601       7.000000
max      8881.635590      20.000000

----------------------------------------

File: 4G_Passive_measurements_sample
Shape: (50000, 26)
Missing Values:
 Date                      0
```

```
Time                     0
UTC                   6808
Latitude                 0
Longitude                0
Altitude              6808
Speed                 6808
EARFCN                   0
Frequency                0
PCI                      0
MNC                      0
CellIdentity             0
eNodeB.ID                0
Power                 1982
SINR                  1982
RSRP                     0
RSRQ                     0
scenario                 0
cellLongitude            0
cellLatitude             0
cellPosErrorLambda1    765
cellPosErrorLambda2      0
n_CellIdentities         0
distance                 0
Band                     0
campaign                 0
dtype: int64

Percentage of Missing Values:
 Date                   0.00
Time                    0.00
UTC                    13.62
Latitude                0.00
Longitude               0.00
Altitude               13.62
Speed                  13.62
EARFCN                  0.00
Frequency               0.00
PCI                     0.00
MNC                     0.00
CellIdentity            0.00
eNodeB.ID               0.00
Power                   3.96
SINR                    3.96
RSRP                    0.00
RSRQ                    0.00
scenario                0.00
cellLongitude           0.00
cellLatitude            0.00
cellPosErrorLambda1     1.53
cellPosErrorLambda2     0.00
n_CellIdentities        0.00
distance                0.00
Band                    0.00
campaign                0.00
dtype: float64

--- DataFrame Info ---
<class 'pandas.core.frame.DataFrame'>
Index: 50000 entries, 206783 to 331229
Data columns (total 26 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Date                 50000 non-null  object
 1   Time                 50000 non-null  object
 2   UTC                  43192 non-null  float64
 3   Latitude             50000 non-null  float64
 4   Longitude            50000 non-null  float64
 5   Altitude             43192 non-null  float64
 6   Speed                43192 non-null  float64
 7   EARFCN               50000 non-null  int64
 8   Frequency            50000 non-null  float64
 9   PCI                  50000 non-null  int64
 10  MNC                  50000 non-null  object
 11  CellIdentity         50000 non-null  int64
 12  eNodeB.ID            50000 non-null  int64
 13  Power                48018 non-null  float64
 14  SINR                 48018 non-null  float64
 15  RSRP                 50000 non-null  float64
 16  RSRQ                 50000 non-null  float64
 17  scenario             50000 non-null  object
 18  cellLongitude        50000 non-null  float64
 19  cellLatitude         50000 non-null  float64
 20  cellPosErrorLambda1  49235 non-null  float64
 21  cellPosErrorLambda2  50000 non-null  float64
 22  n_CellIdentities     50000 non-null  int64
 23  distance             50000 non-null  float64
 24  Band                 50000 non-null  int64
 25  campaign             50000 non-null  object
dtypes: float64(15), int64(6), object(5)
memory usage: 10.3+ MB

--- Summary Statistics ---
                UTC      Latitude     Longitude      Altitude         Speed  \
count  4.319200e+04  50000.000000  50000.000000  43192.000000  43192.000000
mean   1.611759e+09     41.883422     12.485885     69.620841      5.525569
std    1.191589e+06      0.014308      0.022476     41.440891     10.145101
min    1.610528e+09     41.823736     12.418497   -139.740000      0.000000
25%    1.610724e+09     41.871623     12.464796     44.150000      0.680000
50%    1.610979e+09     41.890891     12.494078     65.870000      2.590000
75%    1.612688e+09     41.893862     12.495107     89.590000      4.750000
max    1.614353e+09     41.903102     12.533860    416.550000     76.210000

             EARFCN     Frequency           PCI  CellIdentity      eNodeB.ID  \
count  50000.000000  50000.000000  50000.000000  5.000000e+04   50000.000000
mean    2865.540080   1855.972088    224.401840  4.432288e+07  173136.127900
std     2093.179053    654.085690    143.434373  2.919533e+07  114044.279554
min      501.000000    806.000000      1.000000  1.691931e+07   66091.000000
25%     1225.000000   1807.500000    103.000000  1.771959e+07   69217.000000
50%     1850.000000   1870.000000    198.000000  1.776797e+07   69406.000000
75%     3175.000000   2647.500000    323.000000  7.684507e+07  300176.000000
max     6400.000000   2662.500000    503.000000  7.745152e+07  302545.000000

              Power          SINR          RSRP          RSRQ  cellLongitude  \
count  48018.000000  48018.000000  50000.000000  50000.000000   50000.000000
mean     -75.149779      0.922598    -99.047796    -20.361845      12.486209
std       14.136216     10.626332     14.084812      5.360434       0.022440
min     -121.680000    -20.930000   -142.490000    -45.280000      12.418621
25%      -84.570000     -8.470000   -108.520000    -24.250000      12.467131
50%      -74.850000      2.850000    -99.030000    -19.550000      12.493153
75%      -65.750000      7.330000    -89.680000    -15.880000      12.497913
max      -24.330000     38.840000    -49.470000     -8.650000      12.543056

       cellLatitude  cellPosErrorLambda1  cellPosErrorLambda2  \
count  50000.000000         49235.000000         50000.000000
mean      41.883145            12.750231            12.487935
std        0.015810            13.542108            13.583724
min       41.824584             0.139538             0.000000
25%       41.871271             0.381207             0.246736
50%       41.890689            11.075001            10.810001
75%       41.896503            20.130005            20.130005
max       41.902997           100.000000           100.000000

       n_CellIdentities      distance          Band
count      50000.000000  50000.000000  50000.000000
mean           7.670640    551.831553      7.629300
std            2.972955    795.700295      7.058379
min            1.000000      0.000000      1.000000
25%            5.000000    158.577997      3.000000
50%            8.000000    283.468575      3.000000
75%           10.000000    614.855858      7.000000
max           13.000000   8879.684381     20.000000

----------------------------------------

File: 5G - Passive Measurements
Shape: (8144644, 36)
Missing Values:
 Date                      0
Time                       0
UTC                   519510
Latitude                   0
Longitude                  0
Altitude              519500
Speed                 519510
EARFCN                     0
Frequency                  0
Band                       0
PCI                        0
SSBIdx                     0
SSS-SINR                   0
SSS-RSRP                   0
SSS-RSRQ                   0
```

```
SSS-RePower             0
MNC                     0
DM_RS-SINR             48
DM_RS-RSRP             48
DM_RS-RSRQ             48
DM_RS-RePower          48
PBCH-SINR              48
PBCH-RSRP              48
PBCH-RSRQ              48
PBCH-RePower           48
PSS-SINR                0
PSS-RSRP                0
PSS-RSRQ                0
PSS-RePower             0
SS_PBCH-SINR           48
SS_PBCH-RSRP           48
SS_PBCH-RSRQ           48
SS_PBCH-RePower        48
scenario                0
distance_w         4076613
campaign                0
dtype: int64

Percentage of Missing Values:
 Date                0.00
Time                0.00
UTC                 6.38
Latitude            0.00
Longitude           0.00
Altitude            6.38
Speed               6.38
EARFCN              0.00
Frequency           0.00
Band                0.00
PCI                 0.00
SSBIdx              0.00
SSS-SINR            0.00
SSS-RSRP            0.00
SSS-RSRQ            0.00
SSS-RePower         0.00
MNC                 0.00
DM_RS-SINR          0.00
DM_RS-RSRP          0.00
DM_RS-RSRQ          0.00
DM_RS-RePower       0.00
PBCH-SINR           0.00
PBCH-RSRP           0.00
PBCH-RSRQ           0.00
PBCH-RePower        0.00
PSS-SINR            0.00
PSS-RSRP            0.00
PSS-RSRQ            0.00
PSS-RePower         0.00
SS_PBCH-SINR        0.00
SS_PBCH-RSRP        0.00
SS_PBCH-RSRQ        0.00
SS_PBCH-RePower     0.00
scenario            0.00
distance_w         50.05
campaign            0.00
dtype: float64

--- DataFrame Info ---
<class 'pandas.core.frame.DataFrame'>
Index: 8144644 entries, 1018000 to 451931
Data columns (total 36 columns):
 #   Column           Dtype
---  ------           -----
 0   Date             object
 1   Time             object
 2   UTC              float64
 3   Latitude         float64
 4   Longitude        float64
 5   Altitude         float64
 6   Speed            float64
 7   EARFCN           int64
 8   Frequency        float64
 9   Band             int64
 10  PCI              int64
 11  SSBIdx           int64
 12  SSS-SINR         float64
 13  SSS-RSRP         float64
 14  SSS-RSRQ         float64
 15  SSS-RePower      float64
 16  MNC              object
 17  DM_RS-SINR       float64
 18  DM_RS-RSRP       float64
 19  DM_RS-RSRQ       float64
 20  DM_RS-RePower    float64
 21  PBCH-SINR        float64
 22  PBCH-RSRP        float64
 23  PBCH-RSRQ        float64
 24  PBCH-RePower     float64
 25  PSS-SINR         float64
 26  PSS-RSRP         float64
 27  PSS-RSRQ         float64
 28  PSS-RePower      float64
 29  SS_PBCH-SINR     float64
 30  SS_PBCH-RSRP     float64
 31  SS_PBCH-RSRQ     float64
 32  SS_PBCH-RePower  float64
 33  scenario         object
 34  distance_w       float64
 35  campaign         object
dtypes: float64(27), int64(4), object(5)
memory usage: 2.2+ GB

--- Summary Statistics ---
                UTC      Latitude     Longitude      Altitude         Speed  \
count  7.625134e+06  8.144644e+06  8.144644e+06  7.625144e+06  7.625134e+06
mean   1.611472e+09  4.188311e+01  1.248547e+01  7.114848e+01  4.805149e+00
std    1.092663e+06  1.362870e-02  2.220595e-02  4.463448e+01  9.289222e+00
min    1.610528e+09  4.182374e+01  1.241850e+01 -1.397400e+02  0.000000e+00
25%    1.610653e+09  4.187165e+01  1.246451e+01  4.451000e+01  5.800000e-01
50%    1.610882e+09  4.188967e+01  1.249408e+01  6.608000e+01  2.020000e+00
75%    1.612434e+09  4.189339e+01  1.249504e+01  9.083000e+01  4.430000e+00
max    1.614353e+09  4.190310e+01  1.253385e+01  4.576500e+02  8.208000e+01

             EARFCN     Frequency       Band           PCI        SSBIdx  \
count  8.144644e+06  8.144644e+06  8144644.0  8.144644e+06  8.144644e+06
mean   6.439952e+05  3.659929e+03       78.0  2.040252e+02  2.897570e+00
std    1.751807e+03  2.627710e+01        0.0  1.036128e+02  2.377756e+00
min    6.432960e+05  3.649440e+03       78.0  0.000000e+00  0.000000e+00
25%    6.432960e+05  3.649440e+03       78.0  1.740000e+02  1.000000e+00
50%    6.432960e+05  3.649440e+03       78.0  1.780000e+02  3.000000e+00
75%    6.432960e+05  3.649440e+03       78.0  2.760000e+02  5.000000e+00
max    6.483840e+05  3.725760e+03       78.0  6.550000e+02  7.000000e+00

          SSS-SINR      SSS-RSRP      SSS-RSRQ   SSS-RePower    DM_RS-SINR  \
count  8.144644e+06  8.144644e+06  8.144644e+06  8.144644e+06  8.144596e+06
mean  -9.994347e+00 -1.214935e+02 -2.207226e+01 -1.095772e+02 -9.915880e+00
std    1.041867e+01  1.067987e+01  7.404075e+00  8.346378e+00  1.042048e+01
min   -5.140000e+01 -1.559000e+02 -6.070000e+01 -1.254000e+02 -5.110000e+01
25%   -1.680000e+01 -1.293000e+02 -2.700000e+01 -1.157000e+02 -1.670000e+01
50%   -1.130000e+01 -1.236000e+02 -2.200000e+01 -1.115000e+02 -1.130000e+01
75%   -4.200000e+00 -1.160000e+02 -1.600000e+01 -1.044000e+02 -4.300000e+00
max    4.520000e+01 -5.120000e+01 -1.020000e+01 -5.160000e+01  3.910000e+01

         DM_RS-RSRP    DM_RS-RSRQ  DM_RS-RePower     PBCH-SINR     PBCH-RSRP  \
count  8.144596e+06  8.144596e+06   8.144596e+06  8.144596e+06  8.144596e+06
mean  -1.214775e+02 -2.238280e+01  -1.096387e+02 -9.925716e+00 -1.214816e+02
std    1.070083e+01  7.325926e+00   8.325021e+00  1.041752e+01  1.070502e+01
min   -1.559000e+02 -5.860000e+01  -1.255000e+02 -5.110000e+01 -1.559000e+02
25%   -1.293000e+02 -2.720000e+01  -1.157000e+02 -1.670000e+01 -1.293000e+02
50%   -1.236000e+02 -2.230000e+01  -1.116000e+02 -1.130000e+01 -1.236000e+02
75%   -1.160000e+02 -1.640000e+01  -1.045000e+02 -4.300000e+00 -1.160000e+02
max   -5.140000e+01 -1.060000e+01  -5.180000e+01  4.520000e+01 -5.140000e+01

          PBCH-RSRQ  PBCH-RePower      PSS-SINR      PSS-RSRP      PSS-RSRQ  \
count  8.144596e+06  8.144596e+06  8.144644e+06  8.144644e+06  8.144644e+06
mean  -2.238744e+01 -1.096405e+02 -9.546565e+00 -1.213656e+02 -2.179007e+01
std    7.331567e+00  8.322887e+00  1.072197e+01  1.076002e+01  7.474601e+00
min   -6.140000e+01 -1.250000e+02 -5.150000e+01 -1.559000e+02 -5.980000e+01
25%   -2.720000e+01 -1.157000e+02 -1.660000e+01 -1.293000e+02 -2.680000e+01
50%   -2.230000e+01 -1.116000e+02 -1.110000e+01 -1.235000e+02 -2.180000e+01
75%   -1.640000e+01 -1.045000e+02 -3.500000e+00 -1.158000e+02 -1.550000e+01
max   -1.080000e+01 -5.180000e+01  4.520000e+01 -5.120000e+01 -8.000000e-01

        PSS-RePower  SS_PBCH-SINR  SS_PBCH-RSRP  SS_PBCH-RSRQ  \
count  8.144644e+06  8.144596e+06  8.144596e+06  8.144596e+06
mean  -1.097062e+02 -9.917896e+00 -1.214690e+02 -2.226238e+01
std    8.385293e+00  1.043717e+01  1.070830e+01  7.357874e+00
```

```
min   -1.259000e+02 -5.120000e+01 -1.559000e+02 -5.970000e+01
25%   -1.159000e+02 -1.670000e+01 -1.293000e+02 -2.710000e+01
50%   -1.117000e+02 -1.130000e+01 -1.236000e+02 -2.220000e+01
75%   -1.046000e+02 -4.200000e+00 -1.160000e+02 -1.630000e+01
max   -5.160000e+01  4.520000e+01 -5.140000e+01 -1.060000e+01

       SS_PBCH-RePower    distance_w
count     8.144596e+06  4.068031e+06
mean     -1.096277e+02  2.946099e-02
std       8.332414e+00  1.049546e+00
min      -1.250000e+02  0.000000e+00
25%      -1.157000e+02  0.000000e+00
50%      -1.116000e+02  0.000000e+00
75%      -1.045000e+02  0.000000e+00
max      -5.180000e+01  1.080702e+03

----------------------------------------

File: Latency Tests - Online Gaming - Active Measurements
Shape: (207312, 90)
Missing Values:
 Time                                0
GPS Long                            78234
GPS Lat                             78234
5G  PCI                            193966
LTE PCI                            119486
SS-RSRP                            194689
SS-RSRQ                            194694
SS-SINR                            193968
RSRP                               119538
RSRQ                               119552
SINR                               123312
RAT Info                           183724
5G PDSCH Throughput                192748
LTE PDSCH Throughput               201299
5G  PUSCH Throughput               192495
LTE PUSCH Throughput               203491
5G  PDSCH QPSK Rate                197691
5G  PDSCH 16QAM Rate               197691
5G  PDSCH 64QAM Rate               197691
5G  PDSCH 256QAM Rate              197691
LTE PDSCH QPSK Rate                201299
LTE PDSCH 16QAM Rate               201299
LTE PDSCH 64QAM Rate               201299
LTE PDSCH 256QAM Rate              201299
5G  PUSCH QPSK Rate                194636
5G  PUSCH 16QAM Rate               194636
5G  PUSCH 64QAM Rate               194636
5G  PUSCH 256QAM Rate              194636
LTE PUSCH QPSK Rate                203491
LTE PUSCH 16QAM Rate               203491
LTE PUSCH 64QAM Rate               203491
5G Min PDSCH MCS                   197691
5G Avg PDSCH MCS                   197691
5G Max PDSCH MCS                   197691
LTE DL MCS Level                   130401
5G Min PUSCH MCS                   194640
5G Avg PUSCH MCS                   194640
5G Max PUSCH MCS                   194640
LTE UL MCS Level                   125423
5G Serving SSB Index               193173
5G # Beams                         193173
5G Min Num PDSCH RB                197691
5G Avg Num PDSCH RB                197691
5G Max Num PDSCH RB                197691
LTE PDSCH RB Min                   201299
LTE PDSCH RB Max                   201299
LTE PDSCH RB Average               200465
5G Min Num PUSCH RB                194636
5G Avg Num PUSCH RB                194636
5G Max Num PUSCH RB                194636
LTE PUSCH RB Min                   203491
LTE PUSCH RB Max                   203491
LTE PUSCH RB Average               203491
5G Min PDSCH TBS                   197691
5G Avg PDSCH TBS                   197691
5G Max PDSCH TBS                   197691
LTE PDSCH TBS Min                  201299
LTE PDSCH TBS Max                  201299
LTE PDSCH TBS Average              200465
5G Min PUSCH TBS                   194636
5G Avg PUSCH TBS                   194636
5G Max PUSCH TBS                   194636
LTE PUSCH TBS Min                  203491
LTE PUSCH TBS Max                  203491
LTE PUSCH TBS Average              203491
LTE CA                             119260
LTE CA Type                        119260
DQA Result                         206190
Cur. Num. Sent Packets             194815
Cur. Num. Lost Packets             194815
Cur. Num. Packets not Sent         194815
Cur. Channel QoS 3GPP              194815
Cur. Round Trip Latency Median     194815
Cur. Round Trip Latency 10th       194815
Cur. PDV Median                    194815
Cur. PDV 99.9th                    194815
Cur. Interactivity Score           194815
Num. Sent Packets                  206176
Num. Lost Packets                  206176
Num. Packets not Sent              206176
Channel QoS 3GPP                   206176
Round Trip Latency Median          206176
Round Trip Latency 10th            206176
PDV Median                         206176
PDV 99.9th                         206176
Interactivity Score                206176
UE Mode                                 0
Scenario                                0
Operator                                0
Campaign                                0
dtype: int64

Percentage of Missing Values:
 Time                               0.00
GPS Long                           37.74
GPS Lat                            37.74
5G  PCI                            93.56
LTE PCI                            57.64
SS-RSRP                            93.91
SS-RSRQ                            93.91
SS-SINR                            93.56
RSRP                               57.66
RSRQ                               57.67
SINR                               59.48
RAT Info                           88.62
5G PDSCH Throughput                92.97
LTE PDSCH Throughput               97.10
5G  PUSCH Throughput               92.85
LTE PUSCH Throughput               98.16
5G  PDSCH QPSK Rate                95.36
5G  PDSCH 16QAM Rate               95.36
5G  PDSCH 64QAM Rate               95.36
5G  PDSCH 256QAM Rate              95.36
LTE PDSCH QPSK Rate                97.10
LTE PDSCH 16QAM Rate               97.10
LTE PDSCH 64QAM Rate               97.10
LTE PDSCH 256QAM Rate              97.10
5G  PUSCH QPSK Rate                93.89
5G  PUSCH 16QAM Rate               93.89
5G  PUSCH 64QAM Rate               93.89
5G  PUSCH 256QAM Rate              93.89
LTE PUSCH QPSK Rate                98.16
LTE PUSCH 16QAM Rate               98.16
LTE PUSCH 64QAM Rate               98.16
5G Min PDSCH MCS                   95.36
5G Avg PDSCH MCS                   95.36
5G Max PDSCH MCS                   95.36
LTE DL MCS Level                   62.90
5G Min PUSCH MCS                   93.89
5G Avg PUSCH MCS                   93.89
5G Max PUSCH MCS                   93.89
LTE UL MCS Level                   60.50
5G Serving SSB Index               93.18
5G # Beams                         93.18
5G Min Num PDSCH RB                95.36
5G Avg Num PDSCH RB                95.36
5G Max Num PDSCH RB                95.36
LTE PDSCH RB Min                   97.10
LTE PDSCH RB Max                   97.10
LTE PDSCH RB Average               96.70
5G Min Num PUSCH RB                93.89
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5G Avg Num PUSCH RB              93.89
5G Max Num PUSCH RB              93.89
LTE PUSCH RB Min                 98.16
LTE PUSCH RB Max                 98.16
LTE PUSCH RB Average             98.16
5G Min PDSCH TBS                 95.36
5G Avg PDSCH TBS                 95.36
5G Max PDSCH TBS                 95.36
LTE PDSCH TBS Min                97.10
LTE PDSCH TBS Max                97.10
LTE PDSCH TBS Average            96.70
5G Min PUSCH TBS                 93.89
5G Avg PUSCH TBS                 93.89
5G Max PUSCH TBS                 93.89
LTE PUSCH TBS Min                98.16
LTE PUSCH TBS Max                98.16
LTE PUSCH TBS Average            98.16
LTE CA                           57.53
LTE CA Type                      57.53
DQA Result                       99.46
Cur. Num. Sent Packets           93.97
Cur. Num. Lost Packets           93.97
Cur. Num. Packets not Sent       93.97
Cur. Channel QoS 3GPP            93.97
Cur. Round Trip Latency Median   93.97
Cur. Round Trip Latency 10th     93.97
Cur. PDV Median                  93.97
Cur. PDV 99.9th                  93.97
Cur. Interactivity Score         93.97
Num. Sent Packets                99.45
Num. Lost Packets                99.45
Num. Packets not Sent            99.45
Channel QoS 3GPP                 99.45
Round Trip Latency Median        99.45
Round Trip Latency 10th          99.45
PDV Median                       99.45
PDV 99.9th                       99.45
Interactivity Score              99.45
UE Mode                           0.00
Scenario                          0.00
Operator                          0.00
Campaign                          0.00
dtype: float64

--- DataFrame Info ---
<class 'pandas.core.frame.DataFrame'>
Index: 207312 entries, 16.12.2020 to 15.12.2020
Data columns (total 90 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   Time                            207312 non-null  object
 1   GPS Long                        129078 non-null  float64
 2   GPS Lat                         129078 non-null  float64
 3   5G  PCI                         13346 non-null   float64
 4   LTE PCI                         87826 non-null   float64
 5   SS-RSRP                         12623 non-null   float64
 6   SS-RSRQ                         12618 non-null   float64
 7   SS-SINR                         13344 non-null   float64
 8   RSRP                            87774 non-null   float64
 9   RSRQ                            87760 non-null   float64
 10  SINR                            84000 non-null   float64
 11  RAT Info                        23588 non-null   object
 12  5G PDSCH Throughput             14564 non-null   float64
 13  LTE PDSCH Throughput            6013 non-null    float64
 14  5G  PUSCH Throughput            14817 non-null   float64
 15  LTE PUSCH Throughput            3821 non-null    float64
 16  5G  PDSCH QPSK Rate             9621 non-null    float64
 17  5G  PDSCH 16QAM Rate            9621 non-null    float64
 18  5G  PDSCH 64QAM Rate            9621 non-null    float64
 19  5G  PDSCH 256QAM Rate           9621 non-null    float64
 20  LTE PDSCH QPSK Rate             6013 non-null    float64
 21  LTE PDSCH 16QAM Rate            6013 non-null    float64
 22  LTE PDSCH 64QAM Rate            6013 non-null    float64
 23  LTE PDSCH 256QAM Rate           6013 non-null    float64
 24  5G  PUSCH QPSK Rate             12676 non-null   float64
 25  5G  PUSCH 16QAM Rate            12676 non-null   float64
 26  5G  PUSCH 64QAM Rate            12676 non-null   float64
 27  5G  PUSCH 256QAM Rate           12676 non-null   float64
 28  LTE PUSCH QPSK Rate             3821 non-null    float64
 29  LTE PUSCH 16QAM Rate            3821 non-null    float64
 30  LTE PUSCH 64QAM Rate            3821 non-null    float64
 31  5G Min PDSCH MCS                9621 non-null    float64
 32  5G Avg PDSCH MCS                9621 non-null    float64
 33  5G Max PDSCH MCS                9621 non-null    float64
 34  LTE DL MCS Level                76911 non-null   object
 35  5G Min PUSCH MCS                12672 non-null   float64
 36  5G Avg PUSCH MCS                12672 non-null   float64
 37  5G Max PUSCH MCS                12672 non-null   float64
 38  LTE UL MCS Level                81889 non-null   object
 39  5G Serving SSB Index            14139 non-null   float64
 40  5G # Beams                      14139 non-null   float64
 41  5G Min Num PDSCH RB             9621 non-null    float64
 42  5G Avg Num PDSCH RB             9621 non-null    float64
 43  5G Max Num PDSCH RB             9621 non-null    float64
 44  LTE PDSCH RB Min                6013 non-null    float64
 45  LTE PDSCH RB Max                6013 non-null    float64
 46  LTE PDSCH RB Average            6847 non-null    float64
 47  5G Min Num PUSCH RB             12676 non-null   float64
 48  5G Avg Num PUSCH RB             12676 non-null   float64
 49  5G Max Num PUSCH RB             12676 non-null   float64
 50  LTE PUSCH RB Min                3821 non-null    float64
 51  LTE PUSCH RB Max                3821 non-null    float64
 52  LTE PUSCH RB Average            3821 non-null    float64
 53  5G Min PDSCH TBS                9621 non-null    float64
 54  5G Avg PDSCH TBS                9621 non-null    float64
 55  5G Max PDSCH TBS                9621 non-null    float64
 56  LTE PDSCH TBS Min               6013 non-null    float64
 57  LTE PDSCH TBS Max               6013 non-null    float64
 58  LTE PDSCH TBS Average           6847 non-null    float64
 59  5G Min PUSCH TBS                12676 non-null   float64
 60  5G Avg PUSCH TBS                12676 non-null   float64
 61  5G Max PUSCH TBS                12676 non-null   float64
 62  LTE PUSCH TBS Min               3821 non-null    float64
 63  LTE PUSCH TBS Max               3821 non-null    float64
 64  LTE PUSCH TBS Average           3821 non-null    float64
 65  LTE CA                          88052 non-null   object
 66  LTE CA Type                     88052 non-null   object
 67  DQA Result                      1122 non-null    object
 68  Cur. Num. Sent Packets          12497 non-null   float64
 69  Cur. Num. Lost Packets          12497 non-null   float64
 70  Cur. Num. Packets not Sent      12497 non-null   float64
 71  Cur. Channel QoS 3GPP           12497 non-null   float64
 72  Cur. Round Trip Latency Median  12497 non-null   float64
 73  Cur. Round Trip Latency 10th    12497 non-null   float64
 74  Cur. PDV Median                 12497 non-null   float64
 75  Cur. PDV 99.9th                 12497 non-null   float64
 76  Cur. Interactivity Score        12497 non-null   float64
 77  Num. Sent Packets               1136 non-null    float64
 78  Num. Lost Packets               1136 non-null    float64
 79  Num. Packets not Sent           1136 non-null    float64
 80  Channel QoS 3GPP                1136 non-null    float64
 81  Round Trip Latency Median       1136 non-null    float64
 82  Round Trip Latency 10th         1136 non-null    float64
 83  PDV Median                      1136 non-null    float64
 84  PDV 99.9th                      1136 non-null    float64
 85  Interactivity Score             1136 non-null    float64
 86  UE Mode                         207312 non-null  object
 87  Scenario                        207312 non-null  object
 88  Operator                        207312 non-null  object
 89  Campaign                        207312 non-null  object
dtypes: float64(79), object(11)
memory usage: 143.9+ MB

--- Summary Statistics ---
           GPS Long        GPS Lat       5G  PCI       LTE PCI       SS-RSRP  \
count  129078.000000  129078.000000  13346.000000  87826.000000  12623.000000
mean       12.483803      41.883122    256.864903    238.745144   -103.324131
std         0.026179       0.018403     90.488750    147.634539      8.897926
min        12.427075      41.823743      6.000000      1.000000   -140.000000
25%        12.467300      41.869580    176.000000    126.000000   -110.100000
50%        12.493789      41.893081    261.000000    199.000000   -103.200000
75%        12.500426      41.897505    278.000000    390.000000    -96.500000
max        12.533772      41.900976    441.000000    500.000000    -66.800000

           SS-RSRQ       SS-SINR          RSRP          RSRQ          SINR  \
count  12618.000000  13344.000000  87774.000000  87760.000000  84000.000000
mean     -11.287288     12.588751    -93.233680    -12.237865      5.727202
std        1.621072      8.001845     10.414988      3.356752      7.105887
min      -33.700000    -18.100000   -139.000000    -29.000000    -20.000000
25%      -11.400000      6.700000   -100.000000    -14.000000      0.000000
50%      -10.600000     13.800000    -94.000000    -12.000000      5.000000
75%      -10.400000     18.500000    -86.000000    -10.000000     10.000000
```

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max      -10.100000     42.300000    -52.000000      3.000000     30.000000

       5G PDSCH Throughput  LTE PDSCH Throughput  5G  PUSCH Throughput  \
count         14564.000000          6.013000e+03          14817.000000
mean           1733.758751          3.638307e+03            448.826361
std            2964.311628          4.587418e+04            563.520169
min               0.000000          0.000000e+00              0.000000
25%               0.000000          4.440000e+01              3.792000
50%             146.231500          3.280000e+02            311.292000
75%            2343.817750          6.464000e+02            613.060000
max           18663.750000          1.957440e+06           6909.859000

       LTE PUSCH Throughput  5G  PDSCH QPSK Rate  5G  PDSCH 16QAM Rate  \
count           3821.000000          9621.000000           9621.000000
mean             400.426773            38.206069             12.604099
std              240.552211            45.088258             26.205630
min               12.100000             0.000000              0.000000
25%              244.600000             0.000000              0.000000
50%              359.000000             0.000000              0.000000
75%              447.200000            94.170000             10.000000
max             1330.200000           100.000000            100.000000

       5G  PDSCH 64QAM Rate  5G  PDSCH 256QAM Rate  LTE PDSCH QPSK Rate  \
count           9621.000000           9621.000000          6013.000000
mean              27.044623             22.145197            54.914785
std               41.231965             40.343183            37.643189
min                0.000000              0.000000             0.000000
25%                0.000000              0.000000            17.300000
50%                0.000000              0.000000            50.000000
75%               63.810000              4.850000            99.600000
max              100.000000            100.000000           100.000000

       LTE PDSCH 16QAM Rate  LTE PDSCH 64QAM Rate  LTE PDSCH 256QAM Rate  \
count           6013.000000           6013.000000            6013.000000
mean              25.335074             15.383685               4.361184
std               26.413823             22.277828              15.286486
min                0.000000              0.000000               0.000000
25%                0.000000              0.000000               0.000000
50%               17.000000              2.200000               0.000000
75%               46.900000             25.000000               0.000000
max              100.000000            100.000000             100.000000

       5G  PUSCH QPSK Rate  5G  PUSCH 16QAM Rate  5G  PUSCH 64QAM Rate  \
count         12676.000000          12676.000000          12676.000000
mean              8.046624              8.572341             83.032818
std              24.145087             21.018704             33.727971
min               0.000000              0.000000              0.000000
25%               0.000000              0.000000             92.000000
50%               0.000000              0.000000            100.000000
75%               0.000000              1.000000            100.000000
max             100.000000            100.000000            100.000000

       5G  PUSCH 256QAM Rate  LTE PUSCH QPSK Rate  LTE PUSCH 16QAM Rate  \
count                12676.0          3821.000000           3821.000000
mean                     0.0             7.149019             13.570741
std                      0.0            18.504460             18.273163
min                      0.0             0.000000              0.000000
25%                      0.0             0.000000              0.400000
50%                      0.0             0.200000              5.200000
75%                      0.0             2.600000             21.100000
max                      0.0           100.000000            100.000000

       LTE PUSCH 64QAM Rate  5G Min PDSCH MCS  5G Avg PDSCH MCS  \
count           3821.000000       9621.000000       9621.000000
mean              79.278671          8.781416         11.759692
std               28.831328          8.806450          9.196461
min                0.000000          0.000000          0.000000
25%               72.400000          0.000000          2.000000
50%               92.800000          8.000000         12.000000
75%               99.200000         16.000000         19.000000
max              100.000000         30.000000         30.000000

       5G Max PDSCH MCS  5G Min PUSCH MCS  5G Avg PUSCH MCS  5G Max PUSCH MCS  \
count       9621.000000      12672.000000      12672.000000      12672.000000
mean          20.214323         15.597459         19.463857         26.592882
std           11.644367          6.594036          4.767397          5.563778
min            0.000000          0.000000          0.000000          0.000000
25%            8.000000         12.000000         17.000000         21.000000
50%           29.000000         17.000000         21.000000         30.000000
75%           30.000000         21.000000         22.000000         31.000000
max           31.000000         31.000000         31.000000         31.000000

       5G Serving SSB Index    5G # Beams  5G Min Num PDSCH RB  \
count          14139.000000  14139.000000          9621.000000
mean               1.237782      1.978499            15.641202
std                2.308603      1.336863             3.648903
min                0.000000      1.000000             3.000000
25%                0.000000      1.000000            16.000000
50%                0.000000      1.000000            16.000000
75%                1.000000      4.000000            16.000000
max                7.000000      4.000000           217.000000

       5G Avg Num PDSCH RB  5G Max Num PDSCH RB  LTE PDSCH RB Min  \
count          9621.000000          9621.000000       6013.000000
mean             17.384887            32.659599          3.275403
std               7.773548            33.776181          2.871729
min               3.000000             3.000000          1.000000
25%              16.000000            16.000000          1.000000
50%              16.000000            32.000000          3.000000
75%              17.000000            32.000000          4.000000
max             217.000000           217.000000         86.000000

       LTE PDSCH RB Max  LTE PDSCH RB Average  5G Min Num PUSCH RB  \
count       6013.000000           6847.000000         12676.000000
mean          39.591385              7.719162             3.342379
std           34.810816              8.102673             3.000724
min            2.000000              0.000000             1.000000
25%            9.000000              4.000000             2.000000
50%           28.000000              5.500000             2.000000
75%           60.000000              8.800000             4.000000
max          300.000000            123.800000           164.000000

       5G Avg Num PUSCH RB  5G Max Num PUSCH RB  LTE PUSCH RB Min  \
count         12676.000000         12676.000000       3821.000000
mean              4.166456            10.150600          1.003664
std               5.387917            21.527421          0.060428
min               1.000000             2.000000          1.000000
25%               2.000000             3.000000          1.000000
50%               3.000000             4.000000          1.000000
75%               6.000000             6.000000          1.000000
max             169.000000           215.000000          2.000000

       LTE PUSCH RB Max  LTE PUSCH RB Average  5G Min PDSCH TBS  \
count       3821.000000           3821.000000       9621.000000
mean          35.727820              4.896022        959.688702
std           29.896553              4.665666       1019.157519
min            2.000000              1.300000          0.000000
25%            9.000000              2.200000         69.000000
50%           25.000000              2.900000        688.000000
75%           60.000000              5.200000       1409.000000
max           96.000000             48.400000       6913.000000

       5G Avg PDSCH TBS  5G Max PDSCH TBS  LTE PDSCH TBS Min  \
count       9621.000000       9621.000000        6013.000000
mean        1688.866542       2240.704708         139.991352
std         1361.528623       1701.797696         764.727526
min           10.000000         10.000000          16.000000
25%          333.000000        848.000000          56.000000
50%         1588.000000       2049.000000          72.000000
75%         3057.000000       3585.000000          88.000000
max         9018.000000      30747.000000       48936.000000

       LTE PDSCH TBS Max  LTE PDSCH TBS Average  5G Min PUSCH TBS  \
count        6013.000000            6847.000000      12676.000000
mean         8743.179112               0.070104        171.247476
std          8489.979488               0.883380        155.156142
min            32.000000               0.000000          0.000000
25%          2600.000000               0.000000         92.000000
50%          6712.000000               0.000000         92.000000
75%         12216.000000               0.000000        201.000000
max         68808.000000              32.000000       1122.000000

       5G Avg PUSCH TBS  5G Max PUSCH TBS  LTE PUSCH TBS Min  \
count      12676.000000      12676.000000        3821.000000
mean         237.757258        431.301357         273.088720
std          186.470948        623.623219         253.676869
min           11.000000         11.000000           0.000000
25%          112.000000        153.000000           0.000000
50%          178.000000        201.000000         280.000000
75%          275.250000        592.000000         520.000000
max         3683.000000      19472.000000         776.000000
```

```
       LTE PUSCH TBS Max  LTE PUSCH TBS Average  Cur. Num. Sent Packets  \
count        3821.000000            3821.000000            12497.000000
mean        12523.513216            1880.554829              329.487397
std          9756.945091            1151.525241              304.160461
min           256.000000              80.000000                0.000000
25%          5992.000000            1296.000000              125.000000
50%          8760.000000            1432.000000              343.000000
75%         17568.000000            2200.000000              386.000000
max         66592.000000           13664.000000             1277.000000

       Cur. Num. Lost Packets  Cur. Num. Packets not Sent  \
count            12497.000000                    12497.0
mean                11.391054                        0.0
std                 73.140644                        0.0
min                  0.000000                        0.0
25%                  0.000000                        0.0
50%                  0.000000                        0.0
75%                  0.000000                        0.0
max               1242.000000                        0.0

       Cur. Channel QoS 3GPP  Cur. Round Trip Latency Median  \
count                12497.0                   12497.000000
mean                     0.0                       0.043520
std                      0.0                       0.016806
min                      0.0                       0.000000
25%                      0.0                       0.039000
50%                      0.0                       0.047000
75%                      0.0                       0.053000
max                      0.0                       0.096000

       Cur. Round Trip Latency 10th  Cur. PDV Median  Cur. PDV 99.9th  \
count                 12497.000000     12497.000000     12497.000000
mean                      0.037742         0.010362         0.029483
std                       0.014364         0.005696         0.016522
min                       0.000000         0.000000         0.000000
25%                       0.035000         0.007000         0.020000
50%                       0.041000         0.010000         0.028000
75%                       0.045000         0.013000         0.040000
max                       0.087000         0.051000         0.073000

       Cur. Interactivity Score  Num. Sent Packets  Num. Lost Packets  \
count              12497.000000        1136.000000        1136.000000
mean                  58.172241        3624.651408         125.311620
std                   25.905509           8.781035         445.768745
min                    0.000000        3361.000000           0.000000
25%                   52.700000        3625.000000           0.000000
50%                   66.500000        3625.000000           0.000000
75%                   74.500000        3625.000000          20.000000
max                   90.100000        3626.000000        3542.000000

       Num. Packets not Sent  Channel QoS 3GPP  Round Trip Latency Median  \
count            1136.000000       1136.000000                1136.000000
mean                0.350352         74.194246                   0.049516
std                 8.780864         39.558930                   0.008275
min                 0.000000          0.205000                   0.032000
25%                 0.000000         36.250000                   0.046000
50%                 0.000000        100.000000                   0.050000
75%                 0.000000        100.000000                   0.054000
max               264.000000        100.000000                   0.079000

       Round Trip Latency 10th   PDV Median   PDV 99.9th  Interactivity Score
count              1136.000000  1136.000000  1136.000000          1136.000000
mean                  0.042539     0.014615     0.047716            59.826673
std                   0.006956     0.004566     0.013695            19.466623
min                   0.029000     0.004000     0.014000             0.000000
25%                   0.039000     0.012000     0.036000            54.800000
50%                   0.043000     0.014000     0.048000            64.700000
75%                   0.046000     0.017000     0.060000            69.900000
max                   0.072000     0.036000     0.074000            88.700000

----------------------------------------

File: NB-IoT - Passive Measurements
Shape: (281481, 29)
Missing Values:
 Date                      0
Time                       0
UTC                    22590
Latitude                   0
Longitude                  0
Altitude               22580
Speed                  22590
EARFCN                     0
Frequency                  0
PCI                        0
MNC                        0
CellIdentity               0
eNodeB.ID                  0
NSINR-Tx0              30533
NSINR-Tx1              33152
NRSRP-Tx0              30533
NRSRP-Tx1              33152
NRSRQ-Tx0              30533
NRSRQ-Tx1              33152
NSSS-Power                 0
scenario                   0
cellLongitude              0
cellLatitude               0
cellPosErrorLambda1     7241
cellPosErrorLambda2        0
n_CellIdentities           0
distance                   0
Band                       0
campaign                   0
dtype: int64

Percentage of Missing Values:
 Date                    0.00
Time                     0.00
UTC                      8.03
Latitude                 0.00
Longitude                0.00
Altitude                 8.02
Speed                    8.03
EARFCN                   0.00
Frequency                0.00
PCI                      0.00
MNC                      0.00
CellIdentity             0.00
eNodeB.ID                0.00
NSINR-Tx0               10.85
NSINR-Tx1               11.78
NRSRP-Tx0               10.85
NRSRP-Tx1               11.78
NRSRQ-Tx0               10.85
NRSRQ-Tx1               11.78
NSSS-Power               0.00
scenario                 0.00
cellLongitude            0.00
cellLatitude             0.00
cellPosErrorLambda1      2.57
cellPosErrorLambda2      0.00
n_CellIdentities         0.00
distance                 0.00
Band                     0.00
campaign                 0.00
dtype: float64

--- DataFrame Info ---
<class 'pandas.core.frame.DataFrame'>
Index: 281481 entries, 110097 to 280826
Data columns (total 29 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   Date                 281481 non-null  object
 1   Time                 281481 non-null  object
 2   UTC                  258891 non-null  float64
 3   Latitude             281481 non-null  float64
 4   Longitude            281481 non-null  float64
 5   Altitude             258901 non-null  float64
 6   Speed                258891 non-null  float64
 7   EARFCN               281481 non-null  int64
 8   Frequency            281481 non-null  float64
 9   PCI                  281481 non-null  int64
 10  MNC                  281481 non-null  object
 11  CellIdentity         281481 non-null  int64
 12  eNodeB.ID            281481 non-null  int64
 13  NSINR-Tx0            250948 non-null  float64
 14  NSINR-Tx1            248329 non-null  float64
 15  NRSRP-Tx0            250948 non-null  float64
 16  NRSRP-Tx1            248329 non-null  float64
 17  NRSRQ-Tx0            250948 non-null  float64
```

```
 18  NRSRQ-Tx1            248329 non-null  float64
 19  NSSS-Power           281481 non-null  float64
 20  scenario             281481 non-null  object
 21  cellLongitude        281481 non-null  float64
 22  cellLatitude         281481 non-null  float64
 23  cellPosErrorLambda1  274240 non-null  float64
 24  cellPosErrorLambda2  281481 non-null  float64
 25  n_CellIdentities     281481 non-null  int64
 26  distance             281481 non-null  float64
 27  Band                 281481 non-null  int64
 28  campaign             281481 non-null  object
dtypes: float64(18), int64(6), object(5)
memory usage: 64.4+ MB

--- Summary Statistics ---
                UTC       Latitude      Longitude       Altitude  \
count  2.588910e+05  281481.000000  281481.000000  258901.000000
mean   1.612865e+09      41.876379      12.486588      66.675761
std    7.236656e+05       0.016985       0.028935      34.234850
min    1.611914e+09      41.823736      12.426690     -92.970000
25%    1.612431e+09      41.868493      12.465010      43.720000
50%    1.612692e+09      41.872635      12.493444      64.000000
75%    1.613290e+09      41.893862      12.516384      87.720000
max    1.614353e+09      41.901493      12.533858     350.790000

               Speed         EARFCN      Frequency            PCI  \
count  258891.000000  281481.000000  281481.000000  281481.000000
mean        9.379687    6306.255481     806.625409     256.760677
std        15.204272      49.423335       4.939837     145.880666
min         0.000000    6254.000000     801.402500       8.000000
25%         1.120000    6254.000000     801.402500     137.000000
50%         3.130000    6353.000000     811.297500     266.000000
75%         6.120000    6353.000000     811.297500     375.000000
max        83.880000    6353.000000     811.297500     503.000000

       CellIdentity      eNodeB.ID      NSINR-Tx0      NSINR-Tx1  \
count  2.814810e+05  281481.000000  250948.000000  248329.000000
mean   4.446972e+07  173709.460720      -4.509173      -4.299477
std    2.882168e+07  112584.758301      10.224102      10.236013
min    1.691941e+07   66091.000000     -19.990000     -19.990000
25%    1.768818e+07   69094.000000     -12.330000     -12.110000
50%    1.776856e+07   69408.000000      -6.780000      -6.600000
75%    7.683207e+07  300125.000000       1.340000       1.630000
max    7.745159e+07  302545.000000      34.180000      36.180000

           NRSRP-Tx0      NRSRP-Tx1      NRSRQ-Tx0      NRSRQ-Tx1  \
count  250948.000000  248329.000000  250948.000000  248329.000000
mean      -87.131544     -87.010651     -18.474325     -18.330911
std        13.146805      13.276209       6.740334       6.739038
min      -132.580000    -129.930000     -34.160000     -33.100000
25%       -96.810000     -96.880000     -24.210000     -23.990000
50%       -88.810000     -88.780000     -19.050000     -18.890000
75%       -78.540000     -77.920000     -12.820000     -12.770000
max       -38.180000     -34.750000      -4.400000      -4.400000

          NSSS-Power  cellLongitude   cellLatitude  cellPosErrorLambda1  \
count  281481.000000  281481.000000  281481.000000        274240.000000
mean      -76.679730      12.487087      41.876243             5.208720
std        13.096521       0.028978       0.017796             8.203583
min      -119.400000      12.426546      41.824584             0.164726
25%       -86.320000      12.465303      41.865077             0.240976
50%       -78.440000      12.493074      41.873666             0.483940
75%       -68.090000      12.513037      41.895079             8.656000
max       -25.800000      12.543056      41.901902            37.010002

       cellPosErrorLambda2  n_CellIdentities       distance      Band
count        281481.000000     281481.000000  281481.000000  281481.0
mean              4.951022          2.182741     777.062604      20.0
std               8.195730          0.747385    1062.363397       0.0
min               0.000000          1.000000       0.082859      20.0
25%               0.158733          2.000000     195.416855      20.0
50%               0.274010          2.000000     447.750611      20.0
75%               8.252001          3.000000     866.255229      20.0
max              37.010002          3.000000    8350.743100      20.0

----------------------------------------

File: Throughput Tests - Speedtest - Active Measurements
Shape: (367104, 80)
Missing Values:
 Time                        0
GPS Long                151748
GPS Lat                 151748
5G  PCI                 351760
LTE PCI                 208930
SS-RSRP                 352678
SS-RSRQ                 352678
SS-SINR                 351760
RSRP                    208985
RSRQ                    208982
SINR                    210148
RAT Info                335229
5G PDSCH Throughput     350888
LTE PDSCH Throughput    340180
5G  PUSCH Throughput    349701
LTE PUSCH Throughput    350451
5G  PDSCH QPSK Rate     353830
5G  PDSCH 16QAM Rate    353830
5G  PDSCH 64QAM Rate    353830
5G  PDSCH 256QAM Rate   353830
LTE PDSCH QPSK Rate     340180
LTE PDSCH 16QAM Rate    340180
LTE PDSCH 64QAM Rate    340180
LTE PDSCH 256QAM Rate   340180
5G  PUSCH QPSK Rate     352997
5G  PUSCH 16QAM Rate    352997
5G  PUSCH 64QAM Rate    352997
5G  PUSCH 256QAM Rate   352997
LTE PUSCH QPSK Rate     350451
LTE PUSCH 16QAM Rate    350451
LTE PUSCH 64QAM Rate    350451
5G Min PDSCH MCS        353830
5G Avg PDSCH MCS        353830
5G Max PDSCH MCS        353830
LTE DL MCS Level        216708
5G Min PUSCH MCS        353000
5G Avg PUSCH MCS        353000
5G Max PUSCH MCS        353000
LTE UL MCS Level        214542
5G Serving SSB Index    351354
5G # Beams              351354
5G Min Num PDSCH RB     353830
5G Avg Num PDSCH RB     353830
5G Max Num PDSCH RB     353830
LTE PDSCH RB Min        340180
LTE PDSCH RB Max        340180
LTE PDSCH RB Average    339679
5G Min Num PUSCH RB     352997
5G Avg Num PUSCH RB     352997
5G Max Num PUSCH RB     352997
LTE PUSCH RB Min        350451
LTE PUSCH RB Max        350451
LTE PUSCH RB Average    350451
5G Min PDSCH TBS        353830
5G Avg PDSCH TBS        353830
5G Max PDSCH TBS        353830
LTE PDSCH TBS Min       340180
LTE PDSCH TBS Max       340180
LTE PDSCH TBS Average   339679
5G Min PUSCH TBS        352997
5G Avg PUSCH TBS        352997
5G Max PUSCH TBS        352997
LTE PUSCH TBS Min       350451
LTE PUSCH TBS Max       350451
LTE PUSCH TBS Average   350451
LTE CA                  208691
LTE CA Type             208691
DQA Result              366556
Current Netw. DL        308949
Current Netw. UL        308194
Mean Netw. DL           308949
Mean Netw. UL           308194
Current Netw. DL Avg    308376
Current Netw. DL Max    308376
Current Netw. UL Avg    308171
Current Netw. UL Max    308171
UE Mode                      0
Scenario                     0
Operator                     0
Campaign                     0
dtype: int64
```

```
Percentage of Missing Values:
 Time                      0.00
GPS Long                  41.34
GPS Lat                   41.34
5G  PCI                   95.82
LTE PCI                   56.91
SS-RSRP                   96.07
SS-RSRQ                   96.07
SS-SINR                   95.82
RSRP                      56.93
RSRQ                      56.93
SINR                      57.24
RAT Info                  91.32
5G PDSCH Throughput       95.58
LTE PDSCH Throughput      92.67
5G  PUSCH Throughput      95.26
LTE PUSCH Throughput      95.46
5G  PDSCH QPSK Rate       96.38
5G  PDSCH 16QAM Rate      96.38
5G  PDSCH 64QAM Rate      96.38
5G  PDSCH 256QAM Rate     96.38
LTE PDSCH QPSK Rate       92.67
LTE PDSCH 16QAM Rate      92.67
LTE PDSCH 64QAM Rate      92.67
LTE PDSCH 256QAM Rate     92.67
5G  PUSCH QPSK Rate       96.16
5G  PUSCH 16QAM Rate      96.16
5G  PUSCH 64QAM Rate      96.16
5G  PUSCH 256QAM Rate     96.16
LTE PUSCH QPSK Rate       95.46
LTE PUSCH 16QAM Rate      95.46
LTE PUSCH 64QAM Rate      95.46
5G Min PDSCH MCS          96.38
5G Avg PDSCH MCS          96.38
5G Max PDSCH MCS          96.38
LTE DL MCS Level          59.03
5G Min PUSCH MCS          96.16
5G Avg PUSCH MCS          96.16
5G Max PUSCH MCS          96.16
LTE UL MCS Level          58.44
5G Serving SSB Index      95.71
5G # Beams                95.71
5G Min Num PDSCH RB       96.38
5G Avg Num PDSCH RB       96.38
5G Max Num PDSCH RB       96.38
LTE PDSCH RB Min          92.67
LTE PDSCH RB Max          92.67
LTE PDSCH RB Average      92.53
5G Min Num PUSCH RB       96.16
5G Avg Num PUSCH RB       96.16
5G Max Num PUSCH RB       96.16
LTE PUSCH RB Min          95.46
LTE PUSCH RB Max          95.46
LTE PUSCH RB Average      95.46
5G Min PDSCH TBS          96.38
5G Avg PDSCH TBS          96.38
5G Max PDSCH TBS          96.38
LTE PDSCH TBS Min         92.67
LTE PDSCH TBS Max         92.67
LTE PDSCH TBS Average     92.53
5G Min PUSCH TBS          96.16
5G Avg PUSCH TBS          96.16
5G Max PUSCH TBS          96.16
LTE PUSCH TBS Min         95.46
LTE PUSCH TBS Max         95.46
LTE PUSCH TBS Average     95.46
LTE CA                    56.85
LTE CA Type               56.85
DQA Result                99.85
Current Netw. DL          84.16
Current Netw. UL          83.95
Mean Netw. DL             84.16
Mean Netw. UL             83.95
Current Netw. DL Avg      84.00
Current Netw. DL Max      84.00
Current Netw. UL Avg      83.95
Current Netw. UL Max      83.95
UE Mode                    0.00
Scenario                   0.00
Operator                   0.00
Campaign                   0.00
dtype: float64

--- DataFrame Info ---
<class 'pandas.core.frame.DataFrame'>
Index: 367104 entries, 04.01.2021 to 14.12.2020
Data columns (total 80 columns):
 #   Column                 Non-Null Count   Dtype
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 0   Time                   367104 non-null  object
 1   GPS Long               215356 non-null  float64
 2   GPS Lat                215356 non-null  float64
 3   5G  PCI                15344 non-null   float64
 4   LTE PCI                158174 non-null  float64
 5   SS-RSRP                14426 non-null   float64
 6   SS-RSRQ                14426 non-null   float64
 7   SS-SINR                15344 non-null   float64
 8   RSRP                   158119 non-null  float64
 9   RSRQ                   158122 non-null  float64
 10  SINR                   156956 non-null  float64
 11  RAT Info               31875 non-null   object
 12  5G PDSCH Throughput    16216 non-null   float64
 13  LTE PDSCH Throughput   26924 non-null   float64
 14  5G  PUSCH Throughput   17403 non-null   float64
 15  LTE PUSCH Throughput   16653 non-null   float64
 16  5G  PDSCH QPSK Rate    13274 non-null   float64
 17  5G  PDSCH 16QAM Rate   13274 non-null   float64
 18  5G  PDSCH 64QAM Rate   13274 non-null   float64
 19  5G  PDSCH 256QAM Rate  13274 non-null   float64
 20  LTE PDSCH QPSK Rate    26924 non-null   float64
 21  LTE PDSCH 16QAM Rate   26924 non-null   float64
 22  LTE PDSCH 64QAM Rate   26924 non-null   float64
 23  LTE PDSCH 256QAM Rate  26924 non-null   float64
 24  5G  PUSCH QPSK Rate    14107 non-null   float64
 25  5G  PUSCH 16QAM Rate   14107 non-null   float64
 26  5G  PUSCH 64QAM Rate   14107 non-null   float64
 27  5G  PUSCH 256QAM Rate  14107 non-null   float64
 28  LTE PUSCH QPSK Rate    16653 non-null   float64
 29  LTE PUSCH 16QAM Rate   16653 non-null   float64
 30  LTE PUSCH 64QAM Rate   16653 non-null   float64
 31  5G Min PDSCH MCS       13274 non-null   float64
 32  5G Avg PDSCH MCS       13274 non-null   float64
 33  5G Max PDSCH MCS       13274 non-null   float64
 34  LTE DL MCS Level       150396 non-null  object
 35  5G Min PUSCH MCS       14104 non-null   float64
 36  5G Avg PUSCH MCS       14104 non-null   float64
 37  5G Max PUSCH MCS       14104 non-null   float64
 38  LTE UL MCS Level       152562 non-null  object
 39  5G Serving SSB Index   15750 non-null   float64
 40  5G # Beams             15750 non-null   float64
 41  5G Min Num PDSCH RB    13274 non-null   float64
 42  5G Avg Num PDSCH RB    13274 non-null   float64
 43  5G Max Num PDSCH RB    13274 non-null   float64
 44  LTE PDSCH RB Min       26924 non-null   float64
 45  LTE PDSCH RB Max       26924 non-null   float64
 46  LTE PDSCH RB Average   27425 non-null   float64
 47  5G Min Num PUSCH RB    14107 non-null   float64
 48  5G Avg Num PUSCH RB    14107 non-null   float64
 49  5G Max Num PUSCH RB    14107 non-null   float64
 50  LTE PUSCH RB Min       16653 non-null   float64
 51  LTE PUSCH RB Max       16653 non-null   float64
 52  LTE PUSCH RB Average   16653 non-null   float64
 53  5G Min PDSCH TBS       13274 non-null   float64
 54  5G Avg PDSCH TBS       13274 non-null   float64
 55  5G Max PDSCH TBS       13274 non-null   float64
 56  LTE PDSCH TBS Min      26924 non-null   float64
 57  LTE PDSCH TBS Max      26924 non-null   float64
 58  LTE PDSCH TBS Average  27425 non-null   float64
 59  5G Min PUSCH TBS       14107 non-null   float64
 60  5G Avg PUSCH TBS       14107 non-null   float64
 61  5G Max PUSCH TBS       14107 non-null   float64
 62  LTE PUSCH TBS Min      16653 non-null   float64
 63  LTE PUSCH TBS Max      16653 non-null   float64
 64  LTE PUSCH TBS Average  16653 non-null   float64
 65  LTE CA                 158413 non-null  object
 66  LTE CA Type            158413 non-null  object
 67  DQA Result             548 non-null     object
 68  Current Netw. DL       58155 non-null   float64
 69  Current Netw. UL       58910 non-null   float64
 70  Mean Netw. DL          58155 non-null   float64
 71  Mean Netw. UL          58910 non-null   float64
 72  Current Netw. DL Avg   58728 non-null   float64
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 73  Current Netw. DL Max   58728 non-null   float64
 74  Current Netw. UL Avg   58933 non-null   float64
 75  Current Netw. UL Max   58933 non-null   float64
 76  UE Mode                367104 non-null  object
 77  Scenario               367104 non-null  object
 78  Operator               367104 non-null  object
 79  Campaign               367104 non-null  object
dtypes: float64(69), object(11)
memory usage: 226.9+ MB

--- Summary Statistics ---
           GPS Long        GPS Lat       5G  PCI        LTE PCI  \
count  215356.000000  215356.000000  15344.000000  158174.000000
mean       12.491897      41.877753    209.504367     211.112174
std         0.032500       0.017443     92.578441     153.230632
min        12.426984      41.823736     16.000000       1.000000
25%        12.469472      41.870015    176.000000      73.000000
50%        12.494518      41.875314    240.000000     182.000000
75%        12.522481      41.894910    278.000000     323.000000
max        12.533763      41.900603    655.000000     497.000000

           SS-RSRP       SS-RSRQ       SS-SINR           RSRP           RSRQ  \
count  14426.000000  14426.000000  15344.000000  158119.000000  158122.000000
mean    -101.935166    -10.885027     13.681837     -92.535976     -12.195166
std        8.059901      1.068355      5.953299       9.909350       3.063319
min     -131.500000    -21.200000    -13.200000    -137.000000     -30.000000
25%     -104.700000    -10.800000     11.100000     -99.000000     -14.000000
50%     -100.400000    -10.500000     14.300000     -93.000000     -12.000000
75%      -97.200000    -10.400000     17.500000     -87.000000     -10.000000
max      -57.900000    -10.200000     42.300000     -50.000000       3.000000

               SINR  5G PDSCH Throughput  LTE PDSCH Throughput  \
count  156956.000000         16216.000000          2.692400e+04
mean        8.120894         89613.363801          3.417892e+04
std         7.286532        176166.932246          5.696054e+04
min       -15.000000             0.000000          1.000000e-01
25%         3.000000             8.323250          1.084700e+03
50%         8.000000           757.199500          1.631850e+04
75%        13.000000         20129.588500          5.088680e+04
max        30.000000        739368.000000          5.222080e+06

       5G  PUSCH Throughput  LTE PUSCH Throughput  5G  PDSCH QPSK Rate  \
count          17403.000000          16653.000000         13274.000000
mean            4198.825542          16750.375686            48.708357
std             8913.994487          16315.153514            46.908224
min                0.000000              1.700000             0.000000
25%               32.311000           1163.100000             0.000000
50%              666.278000          13110.800000            50.000000
75%             2024.123500          26880.200000           100.000000
max            70079.216000          71304.100000           100.000000

       5G  PDSCH 16QAM Rate  5G  PDSCH 64QAM Rate  5G  PDSCH 256QAM Rate  \
count          13274.000000          13274.000000           13274.000000
mean               6.449469             17.699742              27.142463
std               17.945195             32.531515              41.475891
min                0.000000              0.000000               0.000000
25%                0.000000              0.000000               0.000000
50%                0.000000              0.000000               0.000000
75%                1.590000             14.290000              72.027500
max              100.000000            100.000000             100.000000

       LTE PDSCH QPSK Rate  LTE PDSCH 16QAM Rate  LTE PDSCH 64QAM Rate  \
count         26924.000000          26924.000000          26924.000000
mean             26.979524             29.082930             34.434122
std              34.288082             26.803794             30.786813
min               0.000000              0.000000              0.000000
25%               0.200000              2.700000              1.800000
50%               8.400000             24.100000             31.300000
75%              46.300000             47.800000             57.500000
max             100.000000            100.000000            100.000000

       LTE PDSCH 256QAM Rate  5G  PUSCH QPSK Rate  5G  PUSCH 16QAM Rate  \
count           26924.000000         14107.000000          14107.000000
mean               9.496449            27.723471             17.940242
std               19.703757            41.428069             33.292878
min                0.000000             0.000000              0.000000
25%                0.000000             0.000000              0.000000
50%                0.000000             0.000000              0.000000
75%                6.800000            68.000000             15.000000
max              100.000000           100.000000            100.000000

       5G  PUSCH 64QAM Rate  5G  PUSCH 256QAM Rate  LTE PUSCH QPSK Rate  \
count          14107.000000                14107.0         16653.000000
mean              53.979301                   0.0            11.216814
std               47.136950                   0.0            24.776561
min                0.000000                   0.0             0.000000
25%                0.000000                   0.0             0.000000
50%               78.000000                   0.0             0.000000
75%              100.000000                   0.0             4.800000
max              100.000000                   0.0           100.000000

       LTE PUSCH 16QAM Rate  LTE PUSCH 64QAM Rate  5G Min PDSCH MCS  \
count          16653.000000          16653.000000      13274.000000
mean              24.337020             64.443536          6.396037
std               33.170382             39.387565          8.123663
min                0.000000              0.000000          0.000000
25%                0.000000             24.000000          0.000000
50%                3.200000             84.200000          1.000000
75%               47.200000            100.000000         14.000000
max              100.000000            100.000000         29.000000

       5G Avg PDSCH MCS  5G Max PDSCH MCS  5G Min PUSCH MCS  5G Avg PUSCH MCS  \
count      13274.000000      13274.000000      14104.000000      14104.000000
mean          11.060494         19.883155         12.751489         17.264606
std            9.632298         12.317529          9.256000          7.696166
min            0.000000          0.000000          0.000000          0.000000
25%            1.000000          5.000000          3.000000         11.000000
50%           10.000000         29.000000         13.500000         19.000000
75%           21.000000         31.000000         23.000000         25.000000
max           29.000000         31.000000         31.000000         31.000000

       5G Max PUSCH MCS  5G Serving SSB Index    5G # Beams  \
count      14104.000000          15750.000000  15750.000000
mean          28.890386              2.751492      2.979175
std            4.202157              2.900003      1.300473
min            0.000000              0.000000      1.000000
25%           29.000000              0.000000      1.000000
50%           30.000000              1.000000      4.000000
75%           31.000000              6.000000      4.000000
max           31.000000              7.000000      4.000000

       5G Min Num PDSCH RB  5G Avg Num PDSCH RB  5G Max Num PDSCH RB  \
count         13274.000000         13274.000000         13274.000000
mean             34.546030            84.622420           108.480714
std              38.813056            88.168235            93.883178
min               3.000000             3.000000             3.000000
25%              16.000000            16.000000            16.000000
50%              16.000000            18.000000            48.000000
75%              16.000000           205.000000           217.000000
max             217.000000           217.000000           217.000000

       LTE PDSCH RB Min  LTE PDSCH RB Max  LTE PDSCH RB Average  \
count      26924.000000      26924.000000          27425.000000
mean          11.513631        106.763037             73.908277
std           19.028753         80.903294             69.812009
min            1.000000          3.000000              0.000000
25%            1.000000         45.000000              6.400000
50%            4.000000         75.000000             61.100000
75%           12.000000        175.000000            123.700000
max          205.000000        350.000000            269.600000

       5G Min Num PUSCH RB  5G Avg Num PUSCH RB  5G Max Num PUSCH RB  \
count         14107.000000         14107.000000         14107.000000
mean             37.375204            49.207840            79.469271
std              66.604417            68.970728            81.416854
min               1.000000             1.000000             2.000000
25%               4.000000             6.000000             6.000000
50%               6.000000             7.000000            36.000000
75%              14.000000            74.000000           153.000000
max             211.000000           211.000000           215.000000

       LTE PUSCH RB Min  LTE PUSCH RB Max  LTE PUSCH RB Average  \
count      16653.000000      16653.000000          16653.000000
mean           9.910106         62.247403             39.296793
std           12.383724         24.229060             26.039331
min            1.000000          3.000000              1.400000
25%            1.000000         40.000000             16.200000
50%            4.000000         64.000000             38.700000
75%           15.000000         90.000000             59.900000
max           81.000000         96.000000             94.700000

       5G Min PDSCH TBS  5G Avg PDSCH TBS  5G Max PDSCH TBS  \
```

```
count      13274.000000      13274.000000      13274.000000
mean        3084.665286      11560.055673      16447.142610
std         5881.707688      16762.419108      20909.906791
min            0.000000         10.000000         10.000000
25%           69.000000        264.000000        672.000000
50%          129.000000       2252.500000       3905.000000
75%         1529.000000      23462.250000      32797.000000
max        52247.000000      66744.000000      90125.000000

       LTE PDSCH TBS Min  LTE PDSCH TBS Max  LTE PDSCH TBS Average  \
count       26924.000000       26924.000000           27425.000000
mean          803.984549       31387.915317              73.943336
std          2586.512475       23809.609252             117.848999
min            16.000000          56.000000               0.000000
25%            56.000000        6968.000000               0.000000
50%           104.000000       29296.000000              32.000000
75%           520.000000       51024.000000              88.000000
max         51024.000000      100752.000000            1032.000000

       5G Min PUSCH TBS  5G Avg PUSCH TBS  5G Max PUSCH TBS  \
count      14107.000000      14107.000000      14107.000000
mean        1373.210321       1772.059687       2872.285532
std         2726.118948       3010.158040       3478.756858
min            0.000000         11.000000         11.000000
25%           92.000000        205.000000        488.000000
50%          333.000000        580.000000       1441.000000
75%          560.000000        967.500000       3969.000000
max        18447.000000      21713.000000      23053.000000

       LTE PUSCH TBS Min  LTE PUSCH TBS Max  LTE PUSCH TBS Average  \
count        16653.00000       16653.000000           16653.000000
mean          5640.69561       32030.187474           20075.706720
std           8063.21882       18417.571465           17136.972346
min              0.00000        1288.000000              88.000000
25%             72.00000       18336.000000            3600.000000
50%           2216.00000       29296.000000           16296.000000
75%           7480.00000       46888.000000           30664.000000
max          59256.00000       71112.000000           69944.000000

       Current Netw. DL  Current Netw. UL  Mean Netw. DL  Mean Netw. UL  \
count      58155.000000      5.891000e+04   58155.000000   58910.000000
mean       38368.389267      7.941421e+03   42093.769590    2886.309245
std       112728.392529      2.005226e+05   69120.204827    4029.962967
min            0.000000      0.000000e+00       0.000000       0.200000
25%           81.700000      6.290000e+01    1855.000000     131.425000
50%          423.800000      2.893000e+02   11541.700000     571.800000
75%        12627.700000      9.444950e+03   39373.000000    4674.750000
max       747060.000000      3.435896e+07  449165.200000   25950.000000

       Current Netw. DL Avg  Current Netw. DL Max  Current Netw. UL Avg  \
count          58728.000000          58728.000000          58933.000000
mean           32292.461090         692145.451226           7088.645733
std             6100.022076         109980.736226           1343.660637
min                0.300000              0.400000              0.400000
25%            28213.150000         706458.600000           6072.000000
50%            30724.500000         747060.000000           7660.900000
75%            36456.400000         747060.000000           7875.700000
max            43958.100000         747060.000000           9482.100000

       Current Netw. UL Max
count          5.893300e+04
mean           2.140802e+07
std            1.662684e+07
min            7.000000e-01
25%            6.405020e+04
50%            3.435896e+07
75%            3.435896e+07
max            3.435896e+07

----------------------------------------
```

The selection of a correct dataset is critical to ensure correct analysis and relevant insights. Among the provided datasets, the 4G - Passive Measurements dataset was chosen for this study since it offers a less missing values and less records which can be useful for efficient analysis and modelling process. Another reason for selecting this dataset is that it is relatively small in comparison with the 5G dataset and thus more manageable in terms of processing through the current computational resources. The selected 4G dataset consists of 527,540 records and it includes both numerical and categorical 26 variables. This combination offers a comprehensive representation of various network conditions. Notably, the missing data values are lower than the other datasets, especially for critical features like signal strength indicators and mobility metrics. On the other hand, this ensures that preprocessing can be conducted efficiently with minimal loss of information (Hossain and Inoue, 2019).

However, the 5G - Passive Measurements dataset contains over 8 million records, which would require a significant amount of computational resources and memory allocation. In additon to this, over 60 variables in the 5G dataset have more than 90% missing values. On the other hand, Latency Tests - Online Gaming and Throughput Tests - Speedtest datasets contain an excessive amount of missing values, which makes them less suitable to perform detailed and reliable analyses. Additionally, the problem of missing values is common in data-driven fields and can often result in decreased model performance, compromising statistical inference. It also leads to biased estimates due to fundamental discrepancies between observed and missing data distributions (Ayilara et al., 2019). Moreover, the NB-IoT - Passive Measurements dataset, though suitable, is less in size and more low-power wide-area network-centric, hence it is less suitable for the objectives of this study. By focusing on the 4G dataset, this study aims to explore the network performance for various scenarios in terms of varying signal power, mobility scenarios, and atmospheric conditions with ensuring efficiency in the computational area.

# 2. Selected Dataset Overview

In [11]:
```
df = pd.read_csv("4G - Passive measurements.csv", index_col=0)  # Read the selected dataset with considering unnamed and irrelevant column with adding index_col parameter
```

In [12]:
```
df.head()
```

Out[12]:

| | Date | Time | UTC | Latitude | Longitude | Altitude | Speed | EARFCN | Frequency | PCI | MNC | CellIdentity | eNodeB.ID | Power | SINR | RSRP | RSRQ | scenario | cellLongitude | cellLatitude | cellPosErrorLambda1 | cellPosErrorLambda2 | n_CellIdentities | distar |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **231098** | 14.01.2021 | 09:19:28.214 | 1.613291e+09 | 41.896722 | 12.507302 | 53.66 | 4.03 | 6300 | 806.0 | 412 | "Op" [1] | 76860425 | 300236 | -54.38 | 6.70 | -78.68 | -19.41 | OW | 12.504280 | 41.890300 | 10.610001 | 10.610001 | 6 | 757.483 |
| **241306** | 14.01.2021 | 09:19:28.214 | 1.613291e+09 | 41.896722 | 12.507302 | 53.66 | 4.03 | 6300 | 806.0 | 411 | "Op" [1] | 76860427 | 300236 | -52.63 | 5.18 | -75.54 | -16.26 | OW | 12.504280 | 41.890300 | 10.610001 | 10.610001 | 6 | 757.483 |
| **291097** | 14.01.2021 | 09:19:28.840 | 1.613291e+09 | 41.896721 | 12.507287 | 54.85 | 4.07 | 1350 | 1820.0 | 272 | "Op" [1] | 76860417 | 300236 | -42.65 | 23.45 | -63.91 | -13.48 | OW | 12.504280 | 41.890300 | 2.392951 | 0.838046 | 6 | 756.968 |
| **741040** | 14.01.2021 | 09:19:36.195 | 1.613291e+09 | 41.896759 | 12.507209 | 54.82 | 4.03 | 3025 | 2647.5 | 266 | "Op" [2] | 17695029 | 69121 | -61.27 | 12.11 | -86.11 | -14.56 | OW | 12.507148 | 41.896951 | 12.490001 | 12.490001 | 6 | 21.962 |
| **781036** | 14.01.2021 | 09:19:36.549 | 1.613291e+09 | 41.896759 | 12.507209 | 54.82 | 4.03 | 6300 | 806.0 | 412 | "Op" [1] | 76860425 | 300236 | -48.81 | 1.44 | -71.21 | -17.41 | OW | 12.504280 | 41.890300 | 10.610001 | 10.610001 | 6 | 758.872 |

The dataset consists of 527,540 records and 26 features covering a wide range of network parameters. This dataset shared by Kousias et al. (2024). They provide a comprehensive dataset of network measurements, covering 4G. Besides, the data was collected over a seven-week period in Rome, Italy, covering a diverse range of urban environments and mobility scenarios. Measurement campaigns were conducted on the infrastructures of two major mobile network operators (MNOs), allowing for the inclusion of heterogeneity in network deployment and end-user experience. Moreover, the table given below indicates features and their descriptions.

| Feature Name | Description | Data Type |
|---|---|---|
| Date, Time | Timestamp of the measurement | Temporal |
| UTC | Coordinated Universal Time in Unix format | Numerical |
| Latitude, Longitude, Altitude | UE (User Equipment) GPS coordinates [in °] | Numerical |
| cellLatitude, cellLongitude | Cell tower GPS coordinates [in °] | Numerical |
| cellPosErrorLambda1, cellPosErrorLambda2 | Estimated error in cell positioning [in meters] | Numerical |
| Speed | Movement speed of the UE [km/h] | Numerical |
| Frequency, EARFCN | Carrier frequency and E-UTRA Absolute RF Channel Number | Numerical |
| MNC | Mobile Network Code (operator identifier) | Categorical |
| PCI | Physical Cell Identifier | Numerical |
| CellIdentity | Cell ID | Numerical |
| eNodeB.ID | Evolved Node B Identifier (base station ID) | Numerical |
| RSRP | Reference Signal Received Power [dBm] | Numerical |
| RSRQ | Reference Signal Received Quality [dB] | Numerical |
| SINR | Signal to Interference and Noise Ratio [dB] | Numerical |
| Power | Received power level [dBm] | Numerical |
| n_CellIdentities | Number of detected Cell IDs per eNodeB | Numerical |
| distance | Line-of-sight distance from the cell [m] | Numerical |
| Band | Radio frequency band identifier | Numerical |
| scenario | Environment classification: Indoor, Outdoor, Vehicle | Categorical |
| campaign | Campaign ID associated with the measurement | Categorical |

# 3. Data Preprocessing & Exploration (Task 1)

### Duplicate Records Check

Initially, a duplicate record check was performed on the dataset, and no duplicate records were found.

In [18]:
```
duplicates = df[df.duplicated(keep=False)]

# Print the number of duplicate rows
print(f"Number of duplicate rows: {duplicates.shape[0]}")
```

```
Number of duplicate rows: 0
```

## 3.1. Basic Dataset Summary & Handling Non-numeric Columns

In [20]:
```
# Basic info about 4G Dataset
print("Dataset Shape:", df.shape)
print("\nDataset Info:\n", df.info())
print("\nMissing Values:\n", df.isnull().sum())
print("\nSummary Statistics:\n", df.describe())
```

```
Dataset Shape: (527540, 26)
<class 'pandas.core.frame.DataFrame'>
Index: 527540 entries, 231098 to 43631
Data columns (total 26 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   Date                 527540 non-null  object 
 1   Time                 527540 non-null  object 
 2   UTC                  457201 non-null  float64
 3   Latitude             527540 non-null  float64
 4   Longitude            527540 non-null  float64
 5   Altitude             457201 non-null  float64
 6   Speed                457201 non-null  float64
 7   EARFCN               527540 non-null  int64  
 8   Frequency            527540 non-null  float64
 9   PCI                  527540 non-null  int64  
 10  MNC                  527540 non-null  object 
 11  CellIdentity         527540 non-null  int64  
 12  eNodeB.ID            527540 non-null  int64  
 13  Power                505826 non-null  float64
 14  SINR                 505826 non-null  float64
 15  RSRP                 527540 non-null  float64
 16  RSRQ                 527540 non-null  float64
 17  scenario             527540 non-null  object 
 18  cellLongitude        527540 non-null  float64
 19  cellLatitude         527540 non-null  float64
 20  cellPosErrorLambda1  519632 non-null  float64
 21  cellPosErrorLambda2  527540 non-null  float64
 22  n_CellIdentities     527540 non-null  int64  
 23  distance             527540 non-null  float64
 24  Band                 527540 non-null  int64  
 25  campaign             527540 non-null  object 
dtypes: float64(15), int64(6), object(5)
memory usage: 108.7+ MB

Dataset Info:
 None

Missing Values:
 Date                       0
Time                       0
UTC                    70339
Latitude                   0
Longitude                  0
Altitude               70339
Speed                  70339
EARFCN                     0
Frequency                  0
PCI                        0
MNC                        0
CellIdentity               0
eNodeB.ID                  0
Power                  21714
SINR                   21714
RSRP                       0
RSRQ                       0
scenario                   0
cellLongitude              0
cellLatitude               0
cellPosErrorLambda1     7908
cellPosErrorLambda2        0
n_CellIdentities           0
distance                   0
Band                       0
campaign                   0
dtype: int64

Summary Statistics:
                UTC       Latitude      Longitude       Altitude  \
count  4.572010e+05  527540.000000  527540.000000  457201.000000   
mean   1.611747e+09      41.883335      12.485928      69.469625   
std    1.184731e+06       0.014385       0.022367      41.151498   
min    1.610528e+09      41.823736      12.418497    -139.740000   
25%    1.610724e+09      41.871599      12.464796      43.870000   
50%    1.610978e+09      41.890723      12.494066      65.650000   
75%    1.612688e+09      41.893862      12.495141      89.340000   
max    1.614353e+09      41.903102      12.533860     416.550000   

              Speed         EARFCN      Frequency            PCI  \
count  457201.000000  527540.000000  527540.000000  527540.000000   
mean        5.523218    2874.847323    1852.404799     224.198226   
std        10.055164    2101.187984     655.671952     143.373641   
min         0.000000     501.000000     806.000000       1.000000   
25%         0.720000    1225.000000    1807.500000     103.000000   
50%         2.590000    1850.000000    1870.000000     198.000000   
75%         4.790000    3175.000000    2647.500000     323.000000   
max        79.270000    6400.000000    2662.500000     503.000000   

       CellIdentity      eNodeB.ID          Power           SINR  \
count  5.275400e+05  527540.000000  505826.000000  505826.000000   
mean   4.442894e+07  173550.426119     -75.152770       0.887128   
std    2.921215e+07  114109.989590      14.170568      10.620611   
min    1.691931e+07   66091.000000    -125.230000     -20.930000   
25%    1.771958e+07   69217.000000     -84.710000      -8.500000   
50%    1.776797e+07   69406.000000     -74.860000       2.820000   
75%    7.684507e+07  300176.000000     -65.700000       7.300000   
max    7.745152e+07  302545.000000     -22.400000      39.020000   

               RSRP           RSRQ  cellLongitude   cellLatitude  \
count  527540.000000  527540.000000  527540.000000  527540.000000   
mean      -99.071670     -20.398189      12.486287      41.883051   
std        14.119162       5.396874       0.022390       0.015900   
min      -145.520000     -49.890000      12.418621      41.824584   
25%      -108.570000     -24.360000      12.467131      41.871271   
50%       -99.100000     -19.550000      12.493153      41.890689   
75%       -89.650000     -15.870000      12.497913      41.896503   
max       -43.170000      -7.990000      12.543056      41.902997   

       cellPosErrorLambda1  cellPosErrorLambda2  n_CellIdentities  \
count        519632.000000        527540.000000     527540.000000   
mean             12.593485            12.335065          7.676123   
std              13.495714            13.537118          2.966718   
min               0.139538             0.000000          1.000000   
25%               0.358485             0.246736          5.000000   
50%              10.810001            10.810001          8.000000   
75%              20.130005            20.130005         10.000000   
max             100.000000           100.000000         13.000000   

            distance           Band  
count  527540.000000  527540.000000  
mean      555.458030       7.667083  
std       796.369764       7.085365  
min         0.000000       1.000000  
25%       158.577997       3.000000  
50%       286.565321       3.000000  
75%       616.922601       7.000000  
max      8881.635590      20.000000  
```

Key signal quality metrics such as RSRP, RSRQ, SINR, and Power are included, alongside spatial indicators like Latitude, Longitude, and Altitude. Network-specific features such as EARFCN, PCI, and CellIdentity are also present. Some variables such as UTC, Altitude, Speed, Power, SINR, and cellPosErrorLambda1 contain missing values, but the majority of features are complete. Summary statistics show that signal strength values (e.g., RSRP and Power) vary significantly across the dataset. The Speed ranges from stationary to over 79 km/h, indicating varying user mobility. Additionally, the values for Frequency and Band suggest that the dataset captures measurements across multiple radio frequencies and cellular bands. These diverse features make the dataset well-suited for both classification and clustering tasks.

### Handling Categorical Columns

In [23]:
```
#columns could be considered as a categorical
cols_to_check = ["EARFCN","MNC", "scenario", "campaign","PCI", "eNodeB.ID", "CellIdentity"]

for col in cols_to_check:
    print(f"Number of Unique values for {col}:")
```

```
    print(df[col].nunique())
    print(f"Top 20 most frequent values for {col}:")
    print(df[col].value_counts(normalize=True).cumsum().head(20).to_frame().reset_index())
    print("\n")
```

```
Number of Unique values for EARFCN:
8
Top 20 most frequent values for EARFCN:
   EARFCN  proportion
0     501    0.152229
1    3025    0.292177
2    1850    0.420072
3    1225    0.542435
4    6400    0.662113
5    6300    0.775416
6    3175    0.888183
7    1350    1.000000


Number of Unique values for MNC:
2
Top 20 most frequent values for MNC:
       MNC  proportion
0  "Op"[2]    0.539751
1  "Op"[1]    1.000000


Number of Unique values for scenario:
3
Top 20 most frequent values for scenario:
  scenario  proportion
0       OW    0.430045
1       IS    0.840727
2       OD    1.000000


Number of Unique values for campaign:
193
Top 20 most frequent values for campaign:
                      campaign  proportion
0            campaign_25_OW_4G    0.024872
1       campaign_6_OW_4G_gaming    0.043125
2   campaign_39_OW_4G_speedtest    0.061347
3            campaign_93_OW_4G    0.077340
4            campaign_94_OW_4G    0.092947
5            campaign_38_OW_4G    0.107685
6            campaign_17_OW_4G    0.122340
7            campaign_40_OW_4G    0.136716
8            campaign_41_OW_4G    0.150527
9   campaign_40_OW_4G_speedtest    0.164295
10           campaign_21_OW_4G    0.178053
11    campaign_20_OW_4G_gaming    0.191747
12           campaign_92_OW_4G    0.205129
13           campaign_24_OW_4G    0.218311
14    campaign_28_OW_4G_gaming    0.231285
15  campaign_21_OW_4G_speedtest    0.243801
16  campaign_17_OW_4G_speedtest    0.256280
17           campaign_57_OW_4G    0.268302
18           campaign_22_OW_4G    0.280049
19  campaign_27_OW_4G_speedtest    0.291534


Number of Unique values for PCI:
466
Top 20 most frequent values for PCI:
    PCI  proportion
0   322    0.037392
1   199    0.053831
2   451    0.070110
3   177    0.085341
4   178    0.099755
5    31    0.113504
6   143    0.126711
7     1    0.139479
8     2    0.151793
9   173    0.164077
10  293    0.176250
11  130    0.188084
12  157    0.198861
13  135    0.209381
14  265    0.219890
15   34    0.229865
16  310    0.239787
17  144    0.249234
18  463    0.258485
19  339    0.267733


Number of Unique values for eNodeB.ID:
242
Top 20 most frequent values for eNodeB.ID:
    eNodeB.ID  proportion
0       69225    0.078654
1      300586    0.139828
2      300064    0.190348
3       67500    0.233563
4       69406    0.275634
5       69217    0.316287
6       69287    0.354398
7      300282    0.385065
8      302257    0.408693
9       67589    0.429188
10      69226    0.447251
11     301593    0.465237
12     300066    0.482926
13      69116    0.500119
14     300109    0.516317
15     300133    0.531366
16      69094    0.545553
17      69266    0.559542
18     302220    0.572891
19      69081    0.586158


Number of Unique values for CellIdentity:
1146
Top 20 most frequent values for CellIdentity:
    CellIdentity  proportion
0       76950106    0.016101
1       76872335    0.031169
2       76950017    0.045974
3       17721611    0.060327
4       76950020    0.073909
5       76950023    0.087116
6       17721612    0.100172
7       17767968    0.112822
8       17280041    0.123259
9       17280042    0.133046
10      17719594    0.142795
11      17280031    0.152186
12      17719606    0.161264
13      17721651    0.169968
14      17767989    0.178608
15      17767987    0.187047
16      76816389    0.195363
17      17720629    0.203431
18      17719593    0.211400
19      77207811    0.219346
```

In [24]:
```
# Categorical columns datatype conversion
categorical_cols = ["EARFCN","MNC", "scenario", "campaign","PCI", "eNodeB.ID", "CellIdentity"]
df[categorical_cols] = df[categorical_cols].astype('category')
```

In this step, several columns were analyzed to determine whether they should be treated as categorical variables. The columns selected for inspection included EARFCN, MNC, scenario, campaign, PCI, eNodeB.ID, and CellIdentity. They represent discrete identifiers or classifications. For each column, the number of unique values and the cumulative frequency of the most common values were examined. Based on this analysis, all listed columns were converted to the categorical data type. This conversion is crucial for improving memory efficiency and ensuring appropriate treatment of these variables in subsequent modeling tasks.

### Handling Time Columns

To streamline temporal processing and enhance interpretability, Date and Time columns were merged into a single DateTime column. This transformation ensured that all timestamp-related information was consolidated in one place, simplifying time-based operations and enabling easier extraction of temporal patterns for subsequent analysis.

Tolidate consistency across time representations, the newly created DateTime column was compared with the existing UTC (Unix Time) column. The difference between the two columns was consistently 30 days for all records. Since both columns effectively carried the same information, the UTC column was dropped to avoid redundancy and potential multicollinearity issues during modeling. odeling.

To further enrich the dataset, a series of new time-related features were engineered from the DateTime column:

- minute

- hour
- day
- month
- day_of_week
- is_weeken
- year

These features were created to capture temporal dynamics that may influence network behavior, such as diurnal usage patterns or weekday/weekend effects. According to Forke and Tropmann-Frick (2021), deriving such features is a crucial aspect of the feature engineering process, especially when raw data lacks semantic clarity.

In [28]:
```
df['DateTime'] = pd.to_datetime(df['Date'] + ' ' + df['Time'], errors='coerce') # creating a new DateTime columns in datetime format
df.drop(['Date', 'Time'], axis=1, inplace=True) ## Since Date and Time information stored in new DateTime columns there no need to keep the old columns
```

In [29]:
```
df["UTC"] = pd.to_datetime(df['UTC'], unit='s') ## converting UTC to datetime format
```

In [30]:
```
df[["UTC","DateTime"]].head(10) ##investigatiing UTC and DateTime Columns
```

Out[30]:

| | UTC | DateTime |
|---|---|---|
| **231098** | 2021-02-14 08:19:27 | 2021-01-14 09:19:28.214 |
| **241306** | 2021-02-14 08:19:27 | 2021-01-14 09:19:28.214 |
| **291097** | 2021-02-14 08:19:28 | 2021-01-14 09:19:28.840 |
| **741040** | 2021-02-14 08:19:35 | 2021-01-14 09:19:36.195 |
| **781036** | 2021-02-14 08:19:35 | 2021-01-14 09:19:36.549 |
| **791009** | 2021-02-14 08:19:35 | 2021-01-14 09:19:36.549 |
| **861008** | 2021-02-14 08:19:39 | 2021-01-14 09:19:39.661 |
| **911025** | 2021-02-14 08:19:41 | 2021-01-14 09:19:41.740 |
| **921033** | 2021-02-14 08:19:41 | 2021-01-14 09:19:41.740 |
| **951004** | 2021-02-14 08:19:43 | 2021-01-14 09:19:43.574 |

In [31]:
```
df["DateDiff"]= df["UTC"]-df["DateTime"] ##creating a new columns which stores time diff between UTC and DateTime columns
```

In [32]:
```
df["DateDiff"].dt.days.value_counts().to_frame().reset_index()  ## investigating the unique day diffs and counts
```

Out[32]:

| | DateDiff | count |
|---|---|---|
| **0** | 30.0 | 457201 |

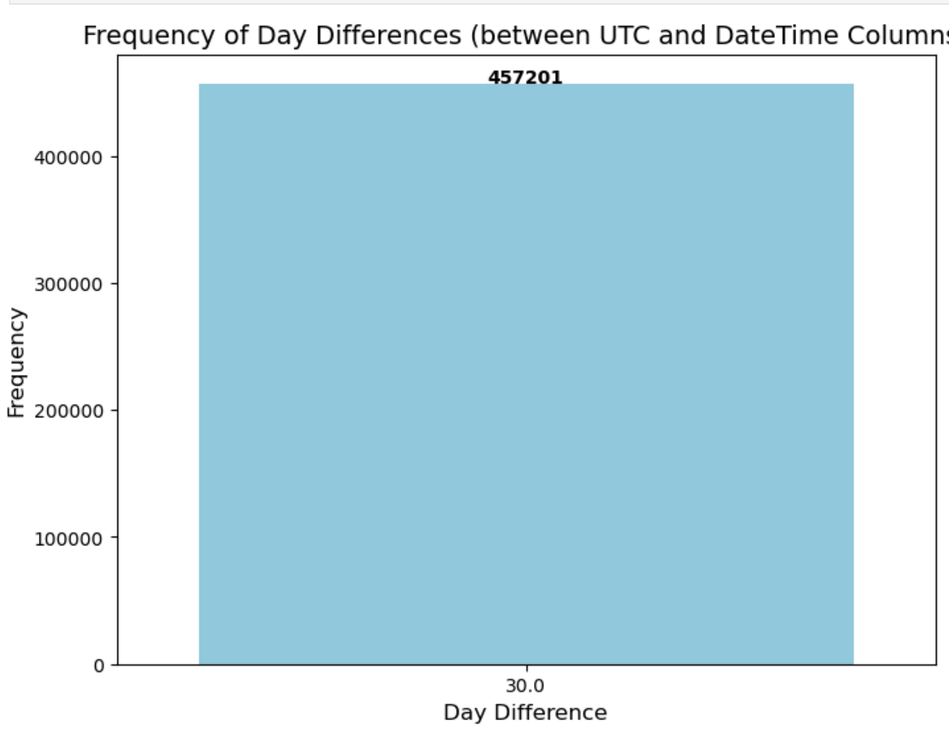
In [33]:
```
# Grouping by unique day differences and counting occurrences
day_counts = df["DateDiff"].dt.days.value_counts().sort_index()

# Creating Bar Chart
plt.figure(figsize=(8, 6))
sns.barplot(x=day_counts.index, y=day_counts.values, color="skyblue")

# Adding text annotations on bars
for index, value in enumerate(day_counts.values):
    plt.text(index, value + 0.5, str(value), ha='center', fontsize=10, fontweight='bold')

# Adjusting titles and labels
plt.title("Frequency of Day Differences (between UTC and DateTime Columns)", fontsize=14)
plt.xlabel("Day Difference", fontsize=12)
plt.ylabel("Frequency", fontsize=12)

# Displaying the plot
plt.show()
```




In [34]:
```
# Creating new time columns
df["minute"] = df["DateTime"].dt.minute
df["hour"] = df["DateTime"].dt.hour
df["day"] = df["DateTime"].dt.day
df["month"] = df["DateTime"].dt.month
df["day_of_week"] = df["DateTime"].dt.dayofweek
df["is_weekend"] = df["day_of_week"].isin([5, 6]).astype(int)
df["year"] = df["DateTime"].dt.year
df["is_weekend"] = df["is_weekend"].astype('category') #converting is_weekend to categorical
```

In [35]:
```
df.drop(columns=["DateDiff", "UTC"], inplace = True) ## Since there is a constant time diff between UTC and DateTime there is no need to keep both of them
```

In [36]:
```
df[["DateTime","minute","hour","day","month","day_of_week","is_weekend","year"]]
```

Out[36]:

| | DateTime | minute | hour | day | month | day_of_week | is_weekend | year |
|---|---|---|---|---|---|---|---|---|
| **231098** | 2021-01-14 09:19:28.214 | 19 | 9 | 14 | 1 | 3 | 0 | 2021 |
| **241306** | 2021-01-14 09:19:28.214 | 19 | 9 | 14 | 1 | 3 | 0 | 2021 |
| **291097** | 2021-01-14 09:19:28.840 | 19 | 9 | 14 | 1 | 3 | 0 | 2021 |
| **741040** | 2021-01-14 09:19:36.195 | 19 | 9 | 14 | 1 | 3 | 0 | 2021 |
| **781036** | 2021-01-14 09:19:36.549 | 19 | 9 | 14 | 1 | 3 | 0 | 2021 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| **43501** | 2020-12-13 11:54:37.247 | 54 | 11 | 13 | 12 | 6 | 1 | 2020 |
| **43521** | 2020-12-13 11:54:37.247 | 54 | 11 | 13 | 12 | 6 | 1 | 2020 |
| **43611** | 2020-12-13 11:54:37.439 | 54 | 11 | 13 | 12 | 6 | 1 | 2020 |
| **43621** | 2020-12-13 11:54:37.439 | 54 | 11 | 13 | 12 | 6 | 1 | 2020 |
| **43631** | 2020-12-13 11:54:37.439 | 54 | 11 | 13 | 12 | 6 | 1 | 2020 |

527540 rows × 8 columns

## 3.2. Missing Values

In the preprocessing phase of this notebook, special attention was paid to handling missing data in a dataset containing 4G passive measurements and a group-based handling missing values approach was implemented based on domain knowledge and exploratory data analysis.

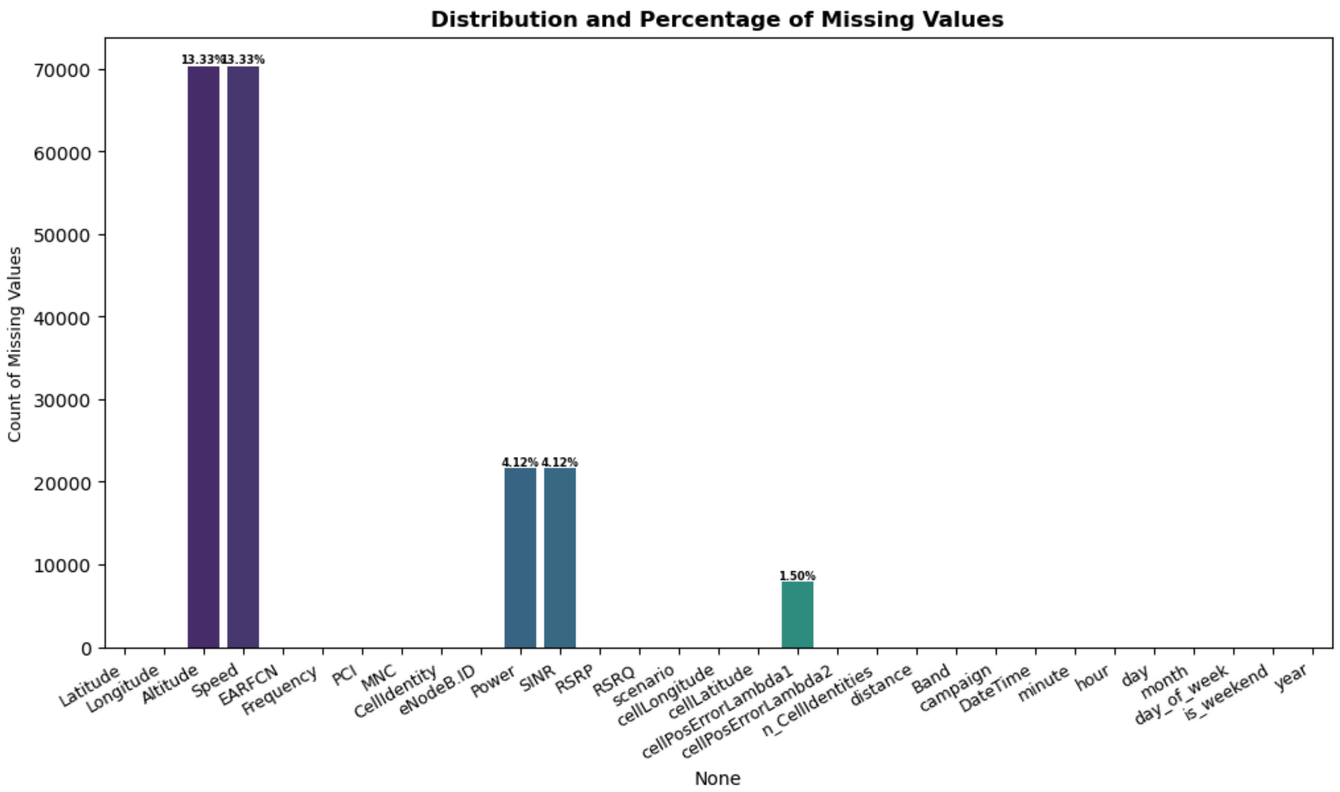
In [39]:
```
# Calculate missing values
missing_counts = df.isnull().sum()
total_rows = len(df)
missing_percent = (missing_counts / total_rows) * 100

# Visualization
plt.figure(figsize=(12,6))
ax = sns.barplot(x=missing_counts.index, y=missing_counts.values, palette="viridis")
```

```
# Add percentages above the bars a
for i, p in enumerate(ax.patches):
    if missing_counts[i] > 0:  # Only add labels for columns with missing values
        ax.annotate(f'{missing_percent[i]:.2f}%',
                    (p.get_x() + p.get_width() / 2., p.get_height()),
                    ha='center', va='bottom', fontsize=6, color='black', fontweight='bold')

# Adjust axis
plt.xticks(rotation=30, ha='right', fontsize=9)  # Rotate and enlarge x-axis labels
plt.ylabel("Count of Missing Values", fontsize=9)
plt.title("Distribution and Percentage of Missing Values", fontsize=12, fontweight='bold')

plt.show()
```

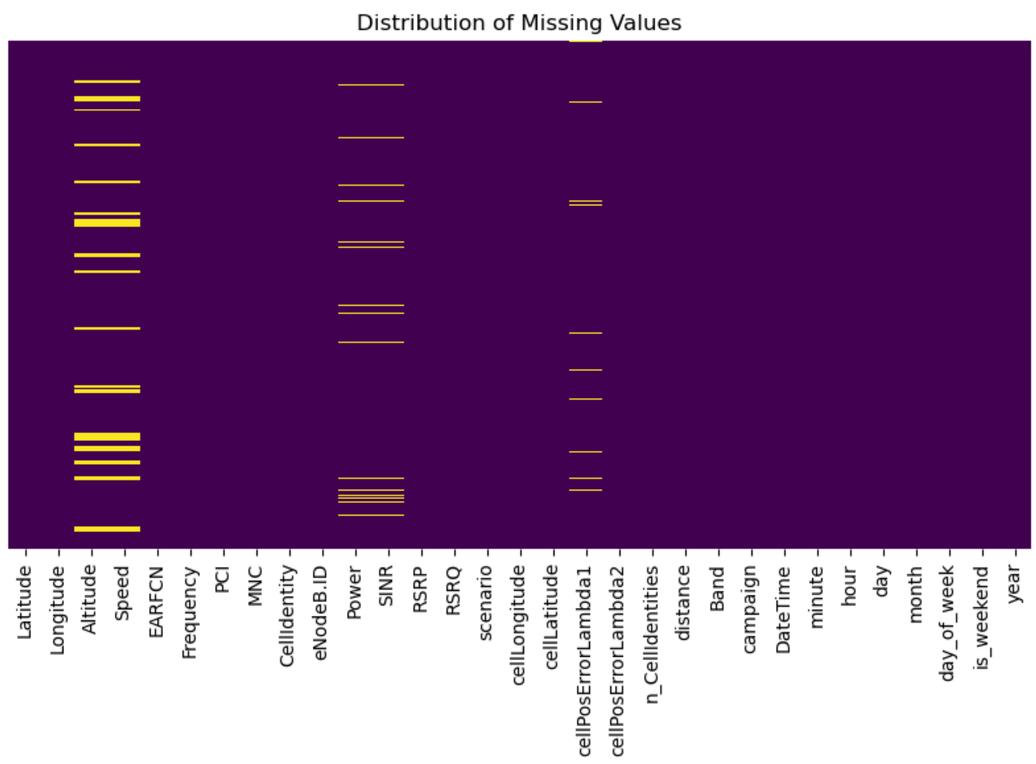



None

As seen in figure above, missing data are included in the columns Speed, Altitude, Power, SINR, and cellPosErrorLambda1. Speed and Altitude had about 13.3% missing value rates, while Power and SINR showed about 4.12% and cellPosErrorLambda1 showed about 1.5% missing records. In addition, the heat map of missing values in figure below reveals patterns that indicate that missing values are not completely random. Therefore, it can be argued that a context-aware strategy would be more appropriate

.

In [41]:
```
# Heatmap for the distribution of missing values
plt.figure(figsize=(10, 5))
sns.heatmap(df.isnull(), cmap='viridis', cbar=False, yticklabels=False)
plt.title("Distribution of Missing Values")
plt.show()
```




In [42]:
```
print(df.isnull().sum())
```

```
Latitude                0
Longitude               0
Altitude            70339
Speed               70339
EARFCN                  0
Frequency               0
PCI                     0
MNC                     0
CellIdentity            0
eNodeB.ID               0
Power               21714
SINR                21714
RSRP                    0
RSRQ                    0
scenario                0
cellLongitude           0
cellLatitude            0
cellPosErrorLambda1  7908
cellPosErrorLambda2     0
n_CellIdentities        0
distance                0
Band                    0
campaign                0
DateTime                0
minute                  0
hour                    0
day                     0
month                   0
day_of_week             0
is_weekend              0
year                    0
dtype: int64
```

In terms of filling missing values, grouped median imputation was applied to preserve the spatial and signal integrity of the data. In detail, Altitude and Speed were filled using the median value in each scenario category. The scenarios represent different collection contexts that may affect the expected range of values of these measurements. Group-based imputation ensures that the filled values reflect the environmental conditions of the original data collection. Power and SINR were filled according to the groupings made by CellIdentity and EARFCN (frequency channel). These features are tightly linked to signal transmission characteristics and cell tower configurations. Estimation within these groups helps maintain network consistency and more accurately reflect real-world radio conditions. Furthermore, cellPosErrorLambda1 was filled using the global median due to its relatively low missing rate and lack of strong grouping relationships.

In [44]:
```
# Filling missing values for Altitude and Speed with the overall median
df['Altitude'] = df.groupby('scenario')['Altitude'].transform(lambda x: x.fillna(x.dropna().median()) if not x.dropna().empty else df['Altitude'].median())
df['Speed'] = df.groupby('scenario')['Speed'].transform(lambda x: x.fillna(x.dropna().median()) if not x.dropna().empty else df['Speed'].median())

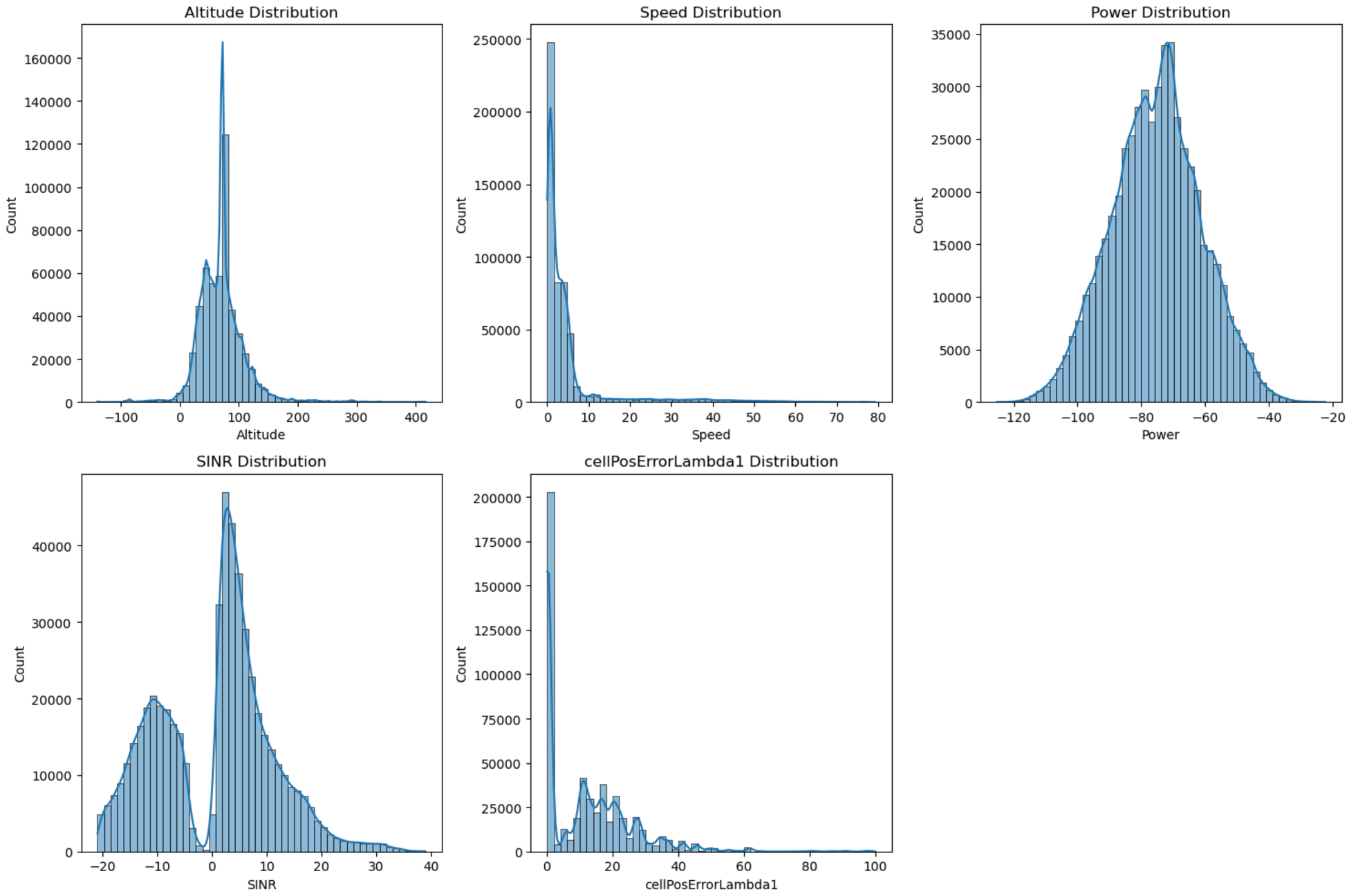

# Filling missing values for Power and SINR based on Cell Identity and Frequency grouping
df['Power'] = df.groupby(['CellIdentity', 'EARFCN'])['Power'].transform(lambda x: x.fillna(x.dropna().median()) if not x.dropna().empty else df['Power'].median())
df['SINR'] = df.groupby(['CellIdentity', 'EARFCN'])['SINR'].transform(lambda x: x.fillna(x.dropna().median()) if not x.dropna().empty else df['SINR'].median())

# Filling missing values for cellPosErrorLambda1 based on median
df['cellPosErrorLambda1'].fillna(df['cellPosErrorLambda1'].median(), inplace=True)

# Final checks  if any missing values remain
print(df.isnull().sum())
```

```
Latitude              0
Longitude             0
Altitude              0
Speed                 0
EARFCN                0
Frequency             0
PCI                   0
MNC                   0
CellIdentity          0
eNodeB.ID             0
Power                 0
SINR                  0
RSRP                  0
RSRQ                  0
scenario              0
cellLongitude         0
cellLatitude          0
cellPosErrorLambda1   0
cellPosErrorLambda2   0
n_CellIdentities      0
distance              0
Band                  0
campaign              0
DateTime              0
minute                0
hour                  0
day                   0
month                 0
day_of_week           0
is_weekend            0
year                  0
dtype: int64
```

In [45]:
```python
# Histograms for columns with missing values
missing_cols = ['Altitude', 'Speed', 'Power', 'SINR', 'cellPosErrorLambda1']

plt.figure(figsize=(15, 10))
for i, col in enumerate(missing_cols, 1):
    plt.subplot(2, 3, i)
    sns.histplot(df[col], bins=50, kde=True)
    plt.title(f'{col} Distribution')
plt.tight_layout()
plt.show()
```




The figureabovew shows that the central tendencies and spread of the imputed features remain consistent with realistic network behaviour. For example, Altitude and Speed maintain reasonable distributions consistent with expected physical motion in real-world scenarios. Furthermore, Power and SINR exhibit typical bell-shaped and multimodal distributions, respectively, consistent with known signal quality profiles in cellular networks. All in all, this strategy not only ensures the completeness of the dataset but also increases its representativeness for subsequent clustering and classification tasks

.

## 3.3. Outlier Detection

In the context of 4G network analysis, the presence of outliers in passive measurement datasets can significantly degrade model training and lead to misleading results (Gil et al., 2019). This section discusses the detection, visualization and handling of outliers in a real-world 4G dataset obtained through the Rohde & Schwarz (R&S) TSMA6 network scanner. In this section two statistical techniques which Interquartile Range (IQR) method and the Z-Score method are examined. To rationalize the application of these two methods, it is important to consider the distributional properties of the dataset. The Z-Score method assumes that the underlying data follow an approximately normal distribution and flags observations as outliers if their standardized values exceed the threshold of $|z| > 3$ (Rousseeuw and Hubert, 2018). However, real-world network data often exhibit skewness, making the Z-Score less effective in such cases. Besides, the IQR method is nonparametric and more robust to skewed distributions. It detects outliers by identifying values in the first quartile (Q1) minus 1.5 times the interquartile range (IQR) or the third quartile (Q3) plus 1.5 times the IQR (Hubert and Van der Veeken, 2008)

.

In [49]:
```python
# Define numeric columns
numeric_cols = df.select_dtypes(include=[np.number]).columns

# Define log scale columns (dBm type columns)
log_scale_cols = ['Power', 'SINR', 'RSRP', 'RSRQ']

# Convert dB and dBm values to linear scale before applying outlier detection
df_log_scaled = df.copy()
df_log_scaled[log_scale_cols] = 10 ** (df_log_scaled[log_scale_cols] / 10)  # Convert dB to linear
```

In [50]:
```python
def detect_outliers(df):
    outlier_counts = pd.DataFrame(index=numeric_cols)

    # IQR Method
    Q1 = df[numeric_cols].quantile(0.25)
    Q3 = df[numeric_cols].quantile(0.75)
    IQR = Q3 - Q1
    iqr_outliers = ((df[numeric_cols] < (Q1 - 1.5 * IQR)) | (df[numeric_cols] > (Q3 + 1.5 * IQR))).sum()
    outlier_counts['IQR'] = iqr_outliers

    # Z-Score Method
    z_scores = np.abs(zscore(df[numeric_cols]))
    z_outliers = (z_scores > 3).sum(axis=0)
    outlier_counts['Z-Score'] = z_outliers

    return outlier_counts
```

In [51]:
```python
# Apply outlier detection on log-transformed dataset
outlier_results = detect_outliers(df_log_scaled)
outlier_results
```

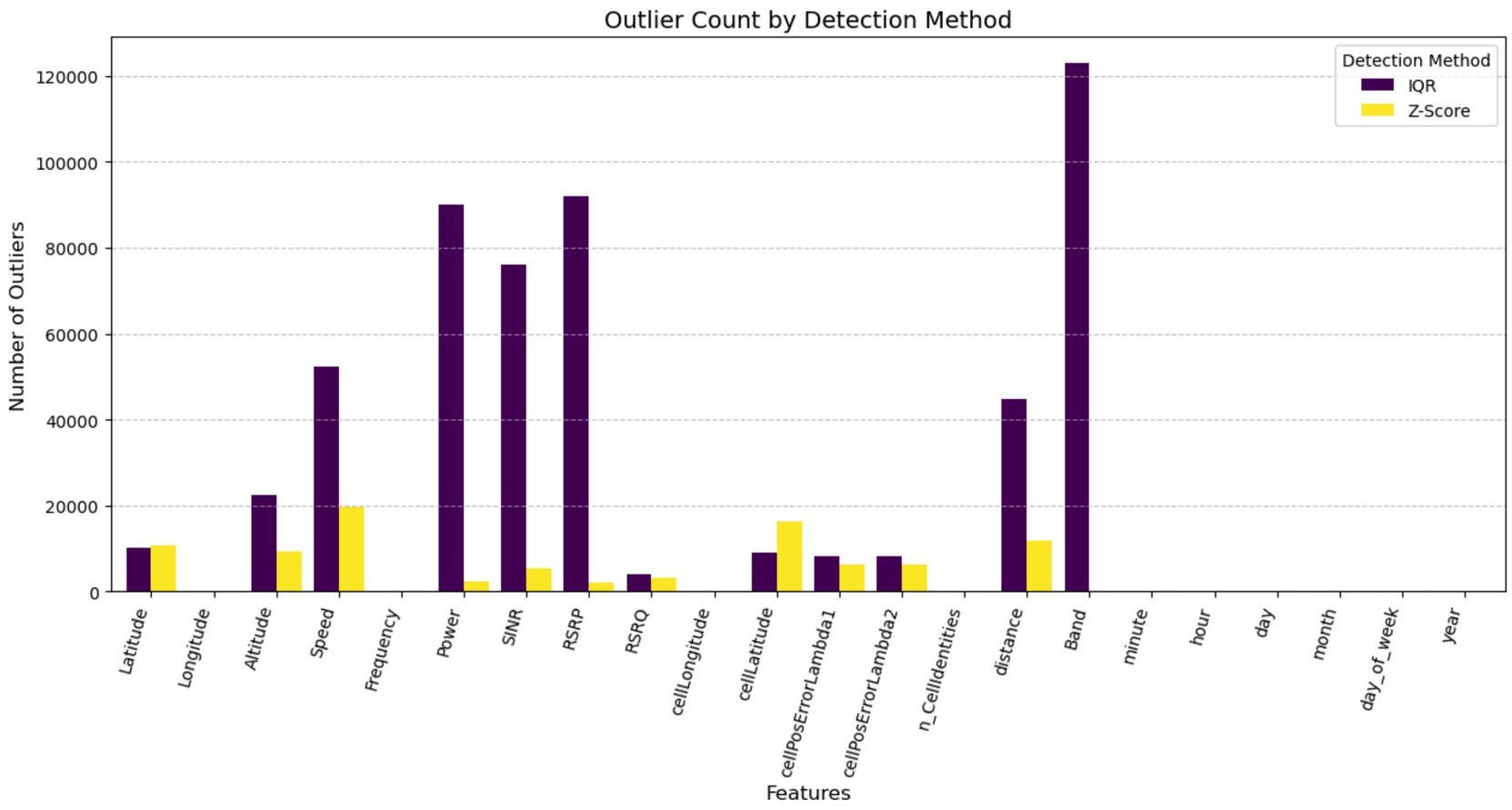
Out[51]:

| | IQR | Z-Score |
|---|---|---|
| **Latitude** | 10228 | 10653 |
| **Longitude** | 258 | 206 |
| **Altitude** | 22505 | 9304 |
| **Speed** | 52364 | 19629 |
| **Frequency** | 0 | 0 |
| **Power** | 90134 | 2340 |
| **SINR** | 76230 | 5379 |
| **RSRP** | 92000 | 1979 |
| **RSRQ** | 4066 | 3331 |
| **cellLongitude** | 236 | 236 |
| **cellLatitude** | 8960 | 16358 |
| **cellPosErrorLambda1** | 8308 | 6259 |
| **cellPosErrorLambda2** | 8308 | 6246 |
| **n_CellIdentities** | 0 | 0 |
| **distance** | 44952 | 11941 |
| **Band** | 122907 | 0 |
| **minute** | 0 | 0 |
| **hour** | 0 | 0 |
| **day** | 0 | 0 |
| **month** | 0 | 0 |
| **day_of_week** | 0 | 0 |
| **year** | 0 | 0 |

In [52]:
```
def plot_outliers(outlier_counts):
    plt.figure(figsize=(15, 8))

    # Visualize the outlier detection results using a bar plot
    outlier_counts.plot(kind='bar', figsize=(15, 6), width=0.8, colormap='viridis')

    # Set plot title and axis labels
    plt.title('Outlier Count by Detection Method', fontsize=14)
    plt.xlabel('Features', fontsize=12)
    plt.ylabel('Number of Outliers', fontsize=12)

    # Rotate column names on the X-axis for better readability
    plt.xticks(rotation=75, ha='right', fontsize=10)

    # Add grid lines to improve readability
    plt.grid(axis='y', linestyle='--', alpha=0.7)

    # Display the plot
    plt.legend(title='Detection Method')
    plt.show()
```

In [53]:
```
plot_outliers(outlier_results)
```

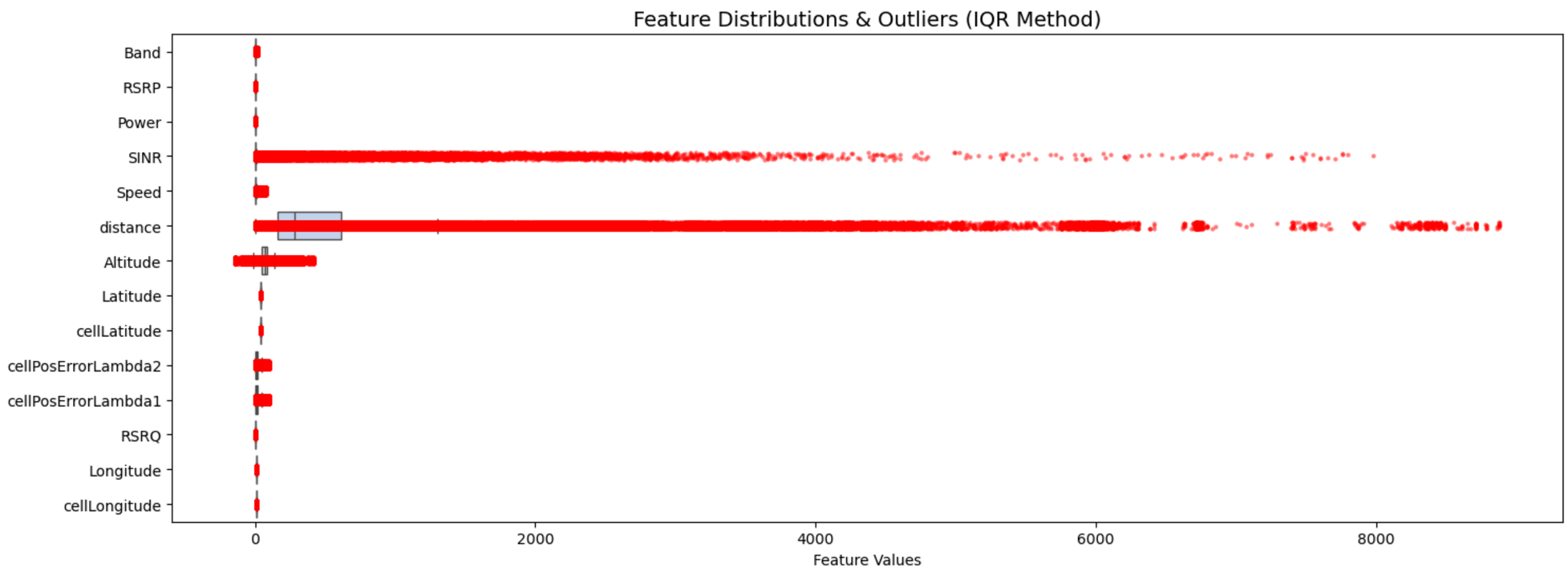
```
<Figure size 1500x800 with 0 Axes>
```

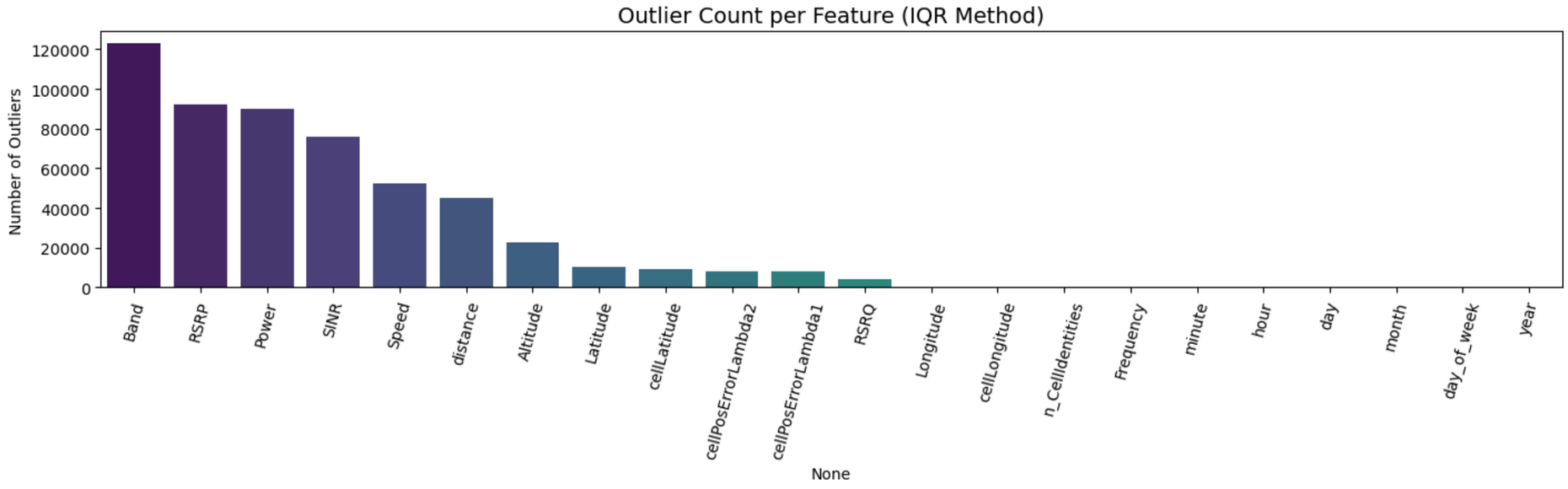


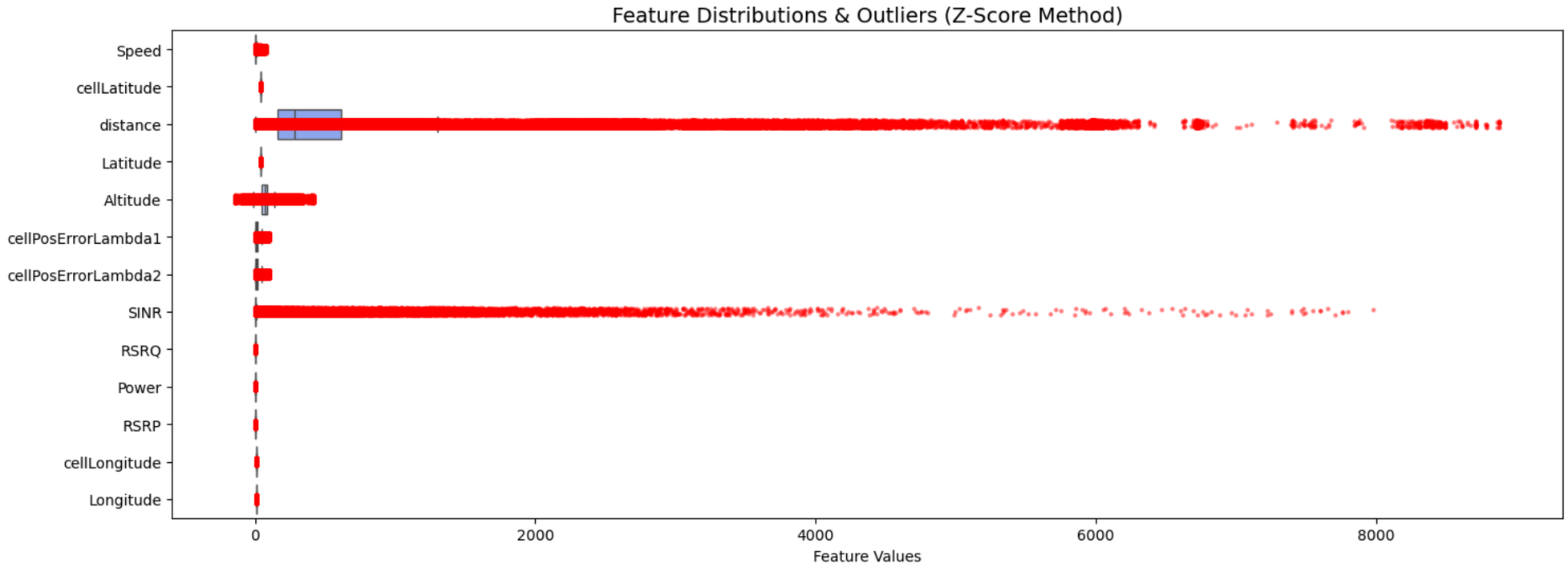

The figure above illustrates the outlier count by applied two detection methods. Before the outlier detection, Power, SINR, RSRP, RSRQ columns were examined by log transformation since they were in dB and dBm types. This stage was a necessary step for detection on a linear basis. The results show that the IQR method identifies significantly more outliers than the Z-Score method for most attributes. For example, attributes such as Band, RSRP, Power, and SINR exhibit exceptionally high outlier frequencies under the IQR method, exceeding 90,000 for the Power column, for example. In contrast, the Z-Score method is more conservative and detects fewer outliers overall. The discrepancy between the two methods is particularly evident for the Band feature, where the IQR method flags more than 120,000 outliers, while Z-Score does not detect any. This suggests that Band has a non-Gaussian distribution, which limits the effectiveness of Z-Score in capturing outliers.

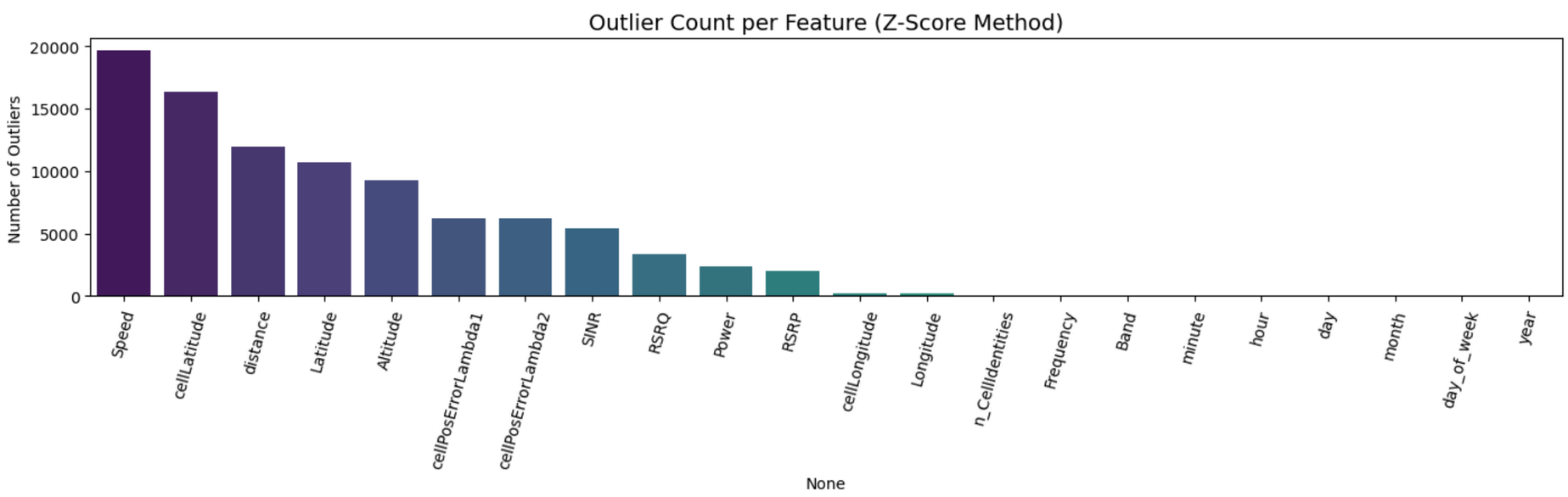
In [55]:
```
def plot_outliers(df, outlier_counts, method="IQR"):
    """
    Plots outliers using IQR or Z-Score method.

    Parameters:
    df (pd.DataFrame): DataFrame containing numerical features.
    outlier_counts (pd.DataFrame): A DataFrame with outlier counts from IQR/Z-Score.
    method (str): "IQR" or "Z-Score" to determine which method's outliers to plot.
    """
    if method not in ["IQR", "Z-Score"]:
        raise ValueError("Invalid method! Choose 'IQR' or 'Z-Score'.")

    outliers = outlier_counts[method].sort_values(ascending=False)  # Sort outliers
    top_features = outliers[outliers > 0].index  # Only features with outliers

    if len(top_features) == 0:
        print(f"No outliers detected using {method} method!")
        return

    fig, axes = plt.subplots(nrows=2, ncols=1, figsize=(15, 10), gridspec_kw={'height_ratios': [2, 1]})

    # 1 Boxplot + Stripplot (Highlight outliers in red)
    plt.sca(axes[0])
    sns.boxplot(data=df[top_features], orient='h', showfliers=False, palette="coolwarm")
    sns.stripplot(data=df[top_features], orient='h', color='red', alpha=0.5, jitter=True, size=3)
    plt.title(f"Feature Distributions & Outliers ({method} Method)", fontsize=14)
    plt.xlabel("Feature Values")

    # 2 Bar Plot (Outlier Count per Feature)
    plt.sca(axes[1])
    sns.barplot(x=outliers.index, y=outliers.values, palette="viridis")
    plt.xticks(rotation=75)
    plt.ylabel("Number of Outliers")
    plt.title(f"Outlier Count per Feature ({method} Method)", fontsize=14)

    plt.tight_layout()
    plt.show()
```

In [56]:
```
# IQR Outliers
plot_outliers(df_log_scaled, outlier_results, method="IQR")
# Z-Score Outliers
plot_outliers(df_log_scaled, outlier_results, method="Z-Score")
```




As seen in figures above, features such as Speed, Distance, and Altitude contain significant high-level outliers, indicating irregularities in user mobility or measurements. Signal-related features such as RSRP and SINR also show significant variability, especially in the lower tail, which may correspond to weak signal conditions or hardware measurement errors. The fact that Z-Score fails to capture most of these anomalies highlights its limitations for skewed or heavy-tailed variables. Meanwhile, the IQR method successfully identifies these irregular data points, making it a more suitable choice for this context.

In [58]:
```
df[numeric_cols].describe()
```

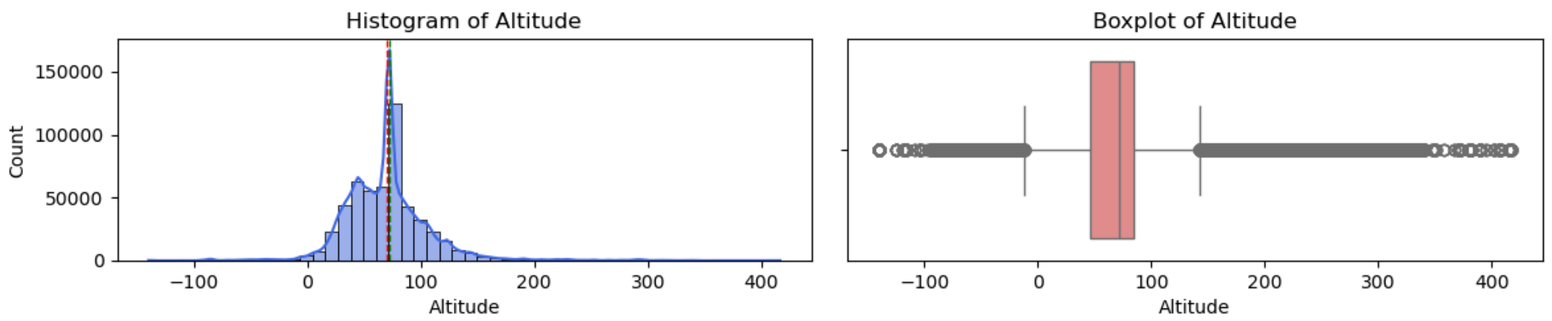
Out[58]:

| | Latitude | Longitude | Altitude | Speed | Frequency | Power | SINR | RSRP | RSRQ | cellLongitude | cellLatitude | cellPosErrorLambda1 | cellPosErrorLambda2 | n_CellIdentities | distance | Band | minu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000000 | 527540.000( |
| **mean** | 41.883335 | 12.485928 | 69.821677 | 4.906786 | 1852.404799 | -75.230305 | 0.698689 | -99.071670 | -20.398189 | 12.486287 | 41.883051 | 12.566750 | 12.335065 | 7.676123 | 555.458030 | 7.667083 | 29.121 |
| **std** | 0.014385 | 0.022367 | 38.320453 | 9.491854 | 655.671952 | 14.081707 | 10.572373 | 14.119162 | 5.396874 | 0.022390 | 0.015900 | 13.395932 | 13.537118 | 2.966718 | 796.369764 | 7.085365 | 17.210 |
| **min** | 41.823736 | 12.418497 | -139.740000 | 0.000000 | 806.000000 | -125.230000 | -20.930000 | -145.520000 | -49.890000 | 12.418621 | 41.824584 | 0.139538 | 0.000000 | 1.000000 | 0.000000 | 1.000000 | 0.000( |
| **25%** | 41.871599 | 12.464796 | 46.290000 | 0.900000 | 1807.500000 | -84.720000 | -8.652500 | -108.570000 | -24.360000 | 12.467131 | 41.871271 | 0.381207 | 0.246736 | 5.000000 | 158.577997 | 3.000000 | 15.000( |
| **50%** | 41.890723 | 12.494066 | 72.010000 | 1.910000 | 1870.000000 | -74.880000 | 2.680000 | -99.100000 | -19.550000 | 12.493153 | 41.890689 | 10.810001 | 10.810001 | 8.000000 | 286.565321 | 3.000000 | 29.000( |
| **75%** | 41.893862 | 12.495141 | 84.990000 | 4.430000 | 2647.500000 | -65.860000 | 7.100000 | -89.650000 | -15.870000 | 12.497913 | 41.896503 | 20.130005 | 20.130005 | 10.000000 | 616.922601 | 7.000000 | 43.000( |
| **max** | 41.903102 | 12.533860 | 416.550000 | 79.270000 | 2662.500000 | -22.400000 | 39.020000 | -43.170000 | -7.990000 | 12.543056 | 41.902997 | 100.000000 | 100.000000 | 13.000000 | 8881.635590 | 20.000000 | 59.000( |

Based on the IQR and Z-Score methods, the features Altitude, RSRP, RSRQ, and distance were flagged as suspicious due to the presence of extreme values. As shown in figure below, their histograms and boxplots were analysed to better understand these distributions. This visual inspection guided the outlier handling process.

In [60]:
```
suspicious_cols = ['Altitude', 'RSRP', 'RSRQ', 'distance']

# visualization
plt.figure(figsize=(12, 10))

# Loop through each column and create a subplot for histograms and boxplots
for i, col in enumerate(suspicious_cols):
    plt.subplot(len(suspicious_cols), 2, 2 * i + 1)
    sns.histplot(df[col], bins=50, kde=True, color='royalblue')
    plt.axvline(df[col].mean(), color='red', linestyle='dashed', linewidth=1)  # Mean line
    plt.axvline(df[col].median(), color='green', linestyle='dashed', linewidth=1)  # Median line
    plt.title(f'Histogram of {col}')
    plt.xlabel(col)
    plt.ylabel('Count')

    plt.subplot(len(suspicious_cols), 2, 2 * i + 2)
```

```
    sns.boxplot(x=df[col], color='lightcoral')
    plt.title(f'Boxplot of {col}')

plt.tight_layout()
plt.show()
```




In outlier handling part, two domain-informed transformations were applied to the features RSRQ and Altitude to address specific types of invalid or physically impossible values. First, RSRQ feature was examined. Any value falling below -30 dB was capped at -30 dB. This decision is grounded in telecommunication engineering principles. In practical LTE and 4G deployments, RSRQ values typically range between -3 dB (excellent signal quality) and -20 dB (poor signal quality) (CableFree, 2025). Values below -30 dB are not only extremely rare but also indicative of measurement errors or sensor noise. Thus, replacing such values with a lower bound of -30 dB serves as a form of value clipping, which helps retain the record while mitigating the influence of spurious signal readings on downstream models. To sum up, this approach preserves the sample distribution while ensuring the integrity of signal quality metrics remains within technically plausible boundaries. After that, Altitude feature was examined. All values below 0 were set to 0. Altitude, representing elevation above sea level, should theoretically be a non-negative quantity. While negative altitudes are possible in specific geological contexts, such cases are unlikely in geographical conditions of Rome (Topographic Map, 2025). Therefore, assigning a minimum of zero ensures physical plausibility and helps prevent the propagation of erroneous geographic data into models that might rely on spatial context.

In [62]:
```
#  Limit RSRQ to -30 dB if it is below -30
df['RSRQ'] = df['RSRQ'].apply(lambda x: -30 if x < -30 else x)

#  Set Altitude to 0 if it is below 0
df['Altitude'] = df['Altitude'].apply(lambda x: 0 if x < 0 else x)
```

## 3.4. Encoding & Normalization

In this step label encoding has performed for categorical variables and standart scaler has used for numerical variables.

In [65]:
```
df_eda = df.copy() # dataframe for Explanatory Data Analysis
df_cla= df.copy()  # dataframe for Classification Task
```

In [66]:
```
categorical_cols = df.select_dtypes(include=["object", "category"]).columns.tolist()
numeric_cols = df.select_dtypes(include=["int64", "float64", "int32"]).columns.tolist()
```

In [67]:
```
# create label encoder object
le = LabelEncoder()
for col in categorical_cols:
    df[col] = le.fit_transform(df[col])
    df_cla[col] = le.fit_transform(df_cla[col])
```

In [68]:
```
# StandardScaler object
scaler = StandardScaler()

for col in numeric_cols:
    df_cla[col] = scaler.fit_transform(df_cla[col].values.reshape(-1, 1))
```

In [69]:
```
total_columns = len(categorical_cols) + len(numeric_cols)
print(f"Categorical Columns: {len(categorical_cols)}, Numerical Columns: {len(numeric_cols)}, Total Columns: {total_columns}")
```

```
Categorical Columns: 8, Numerical Columns: 22, Total Columns: 30
```

In [70]:
```
print("Encoded & Scaled DataFrame:")
df_cla.head()
```

```
Encoded & Scaled DataFrame:
```

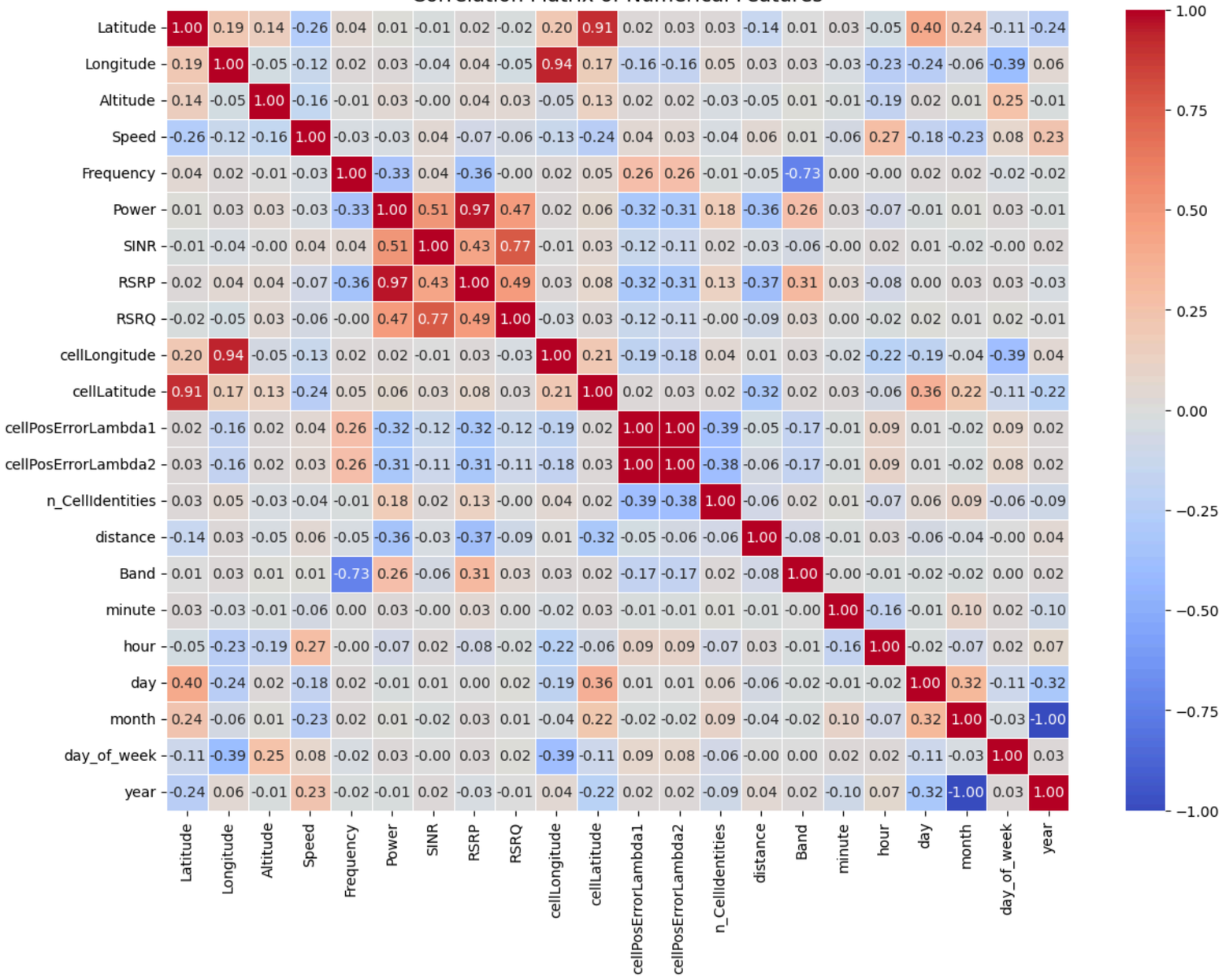
Out[70]:

| | Latitude | Longitude | Altitude | Speed | EARFCN | Frequency | PCI | MNC | CellIdentity | eNodeB.ID | Power | SINR | RSRP | RSRQ | scenario | cellLongitude | cellLatitude | cellPosErrorLambda1 | cellPosErrorLambda2 | n_CellIdentities | distance | Band | campaign |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **231098** | 0.930621 | 0.955628 | -0.452221 | -0.092373 | 6 | -1.595929 | 381 | 0 | 914 | 165 | 1.480667 | 0.567641 | 1.444256 | 0.170094 | 2 | 0.803609 | 0.455923 | -0.146071 | -0.127432 | -0.564976 | 0.253684 | 1.740620 | 153 |
| **241306** | 0.930621 | 0.955628 | -0.452221 | -0.092373 | 6 | -1.595929 | 380 | 0 | 916 | 165 | 1.604942 | 0.423870 | 1.666649 | 0.782559 | 2 | 0.803609 | 0.455923 | -0.146071 | -0.127432 | -0.564976 | 0.253684 | 1.740620 | 153 |
| **291097** | 0.930552 | 0.954957 | -0.419966 | -0.088158 | 2 | -0.049422 | 254 | 0 | 911 | 165 | 2.313664 | 2.151961 | 2.490354 | 1.323084 | 2 | 0.803609 | 0.455923 | -0.759470 | -0.849297 | -0.564976 | 0.253037 | -0.658694 | 153 |
| **741040** | 0.933193 | 0.951470 | -0.420779 | -0.092373 | 4 | 1.212643 | 248 | 1 | 378 | 59 | 0.991380 | 1.079353 | 0.918021 | 1.113096 | 2 | 0.931703 | 0.874233 | -0.005729 | 0.011445 | -0.564976 | -0.669909 | -0.094150 | 153 |
| **781036** | 0.933193 | 0.951470 | -0.420779 | -0.092373 | 6 | -1.595929 | 381 | 0 | 914 | 165 | 1.876216 | 0.070118 | 1.973325 | 0.558961 | 2 | 0.803609 | 0.455923 | -0.146071 | -0.127432 | -0.564976 | 0.255428 | 1.740620 | 153 |

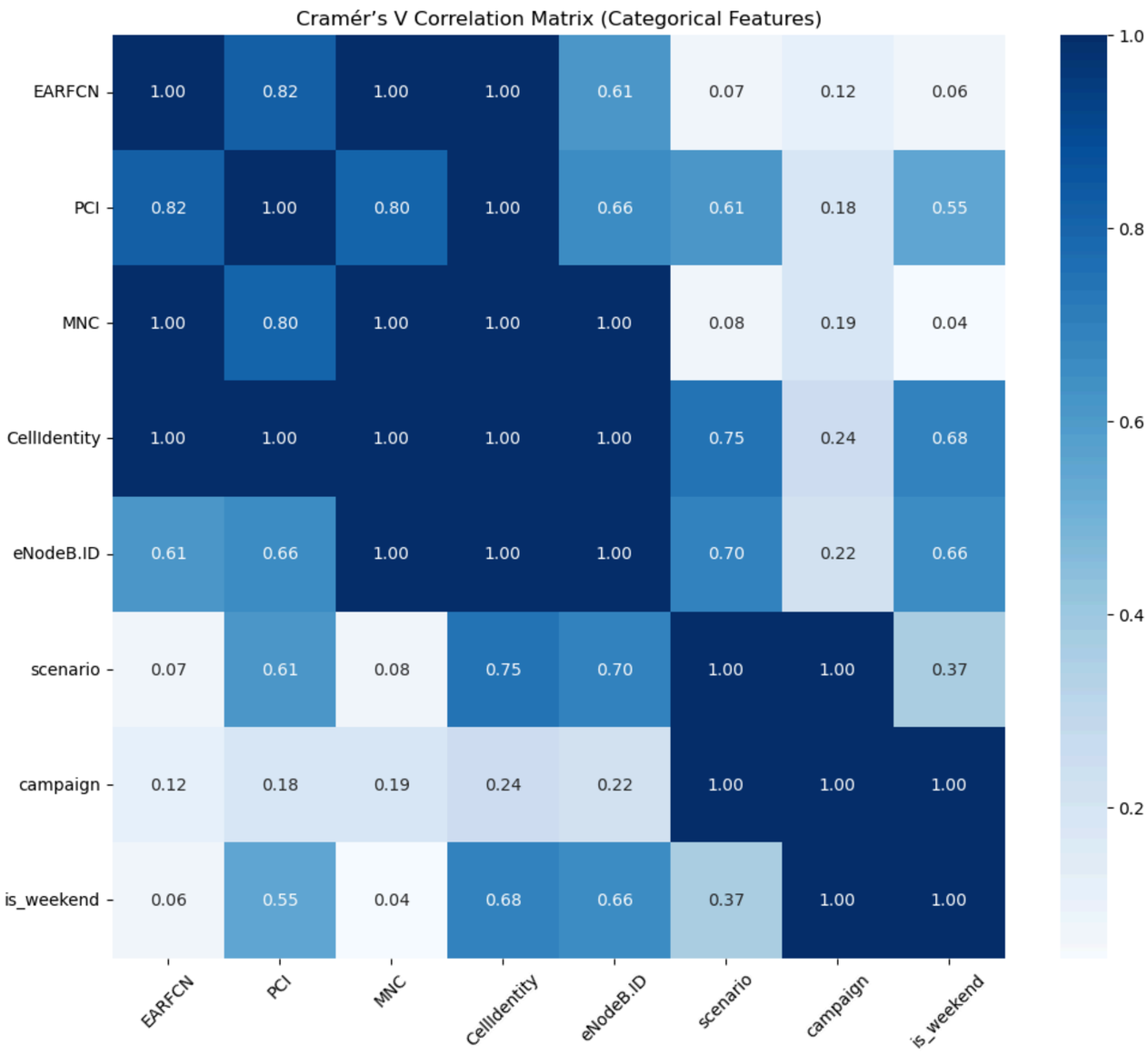
## 3.5. Data Visualizations

In this study, Pearson's Correlation was used to analyse the numerical columns. In this case, the correlation matrix systematically quantifies linear relationships between multiple numeric variables by evaluating their relationships on a standard scale and this process ranging from -1 to 1 (Alshammari, 2024). Furthermore, this step facilitates informed decision making in statistical modelling and feature selection by allowing them to detect dependencies and identify patterns in the data. The results of the applied correlation matrix provided a comprehensive overview of the linear relationships between numerical features in the dataset. Figure 2.10 illustrates the correlation matrix of numerical features. For instance, power shows strong positive correlations with RSRP (0.97) and RSRQ (0.77). This indicates that signal strength measurements are closely linked and may affect each other. In addition, SINR also shows a moderate correlation with Power (0.77), indicating its dependence on signal strength quality.

In [73]:
```
# Correlation heatmap
plt.figure(figsize=(14, 10))
sns.heatmap(df_eda[numeric_cols].corr(), annot=True, fmt=".2f", cmap="coolwarm", linewidths=0.5)
plt.title("Correlation Matrix of Numerical Features", fontsize=14)
plt.show()
```



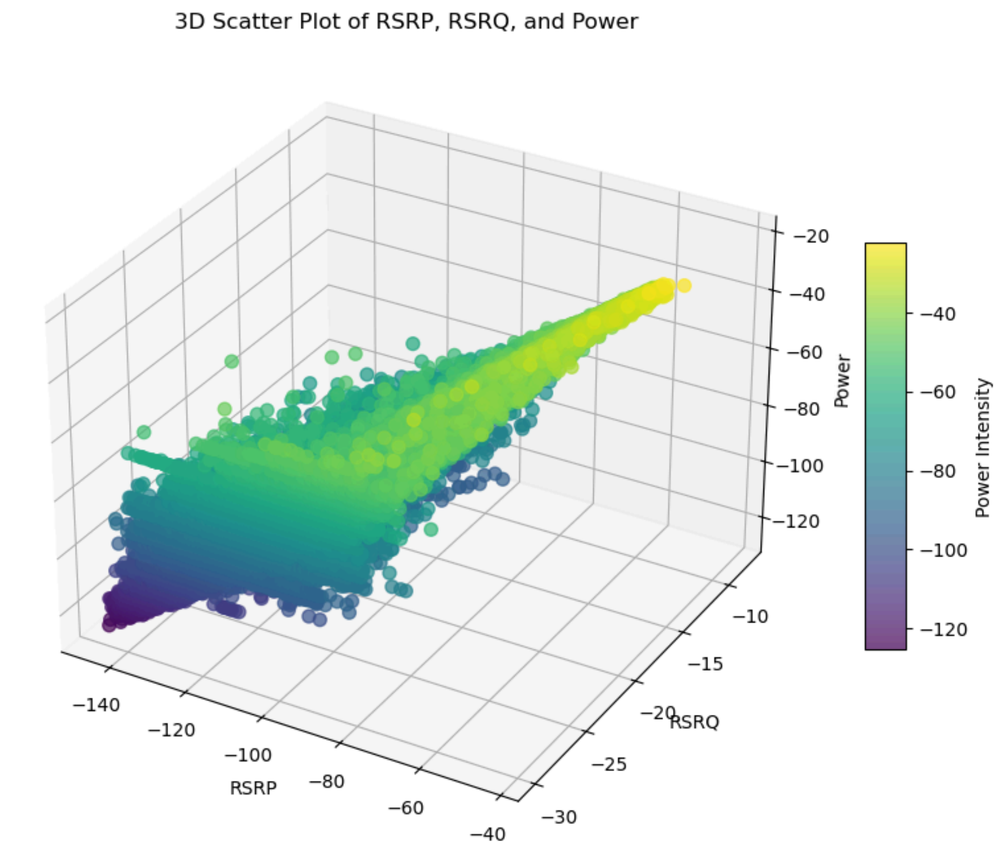

In [74]:
```python
def cramers_v(x, y):
    confusion_matrix = pd.crosstab(x, y)
    chi2 = chi2_contingency(confusion_matrix, correction=False)[0]
    n = confusion_matrix.sum().sum()
    phi2 = chi2/n
    r, k = confusion_matrix.shape
    phi2corr = max(0, phi2 - ((k-1)*(r-1))/(n-1))
    rcorr = r - ((r-1)**2)/(n-1)
    kcorr = k - ((k-1)**2)/(n-1)
    return np.sqrt(phi2corr / min((kcorr-1), (rcorr-1)))

# Cramer's V Matrix for Categorical Features
cramers_results = pd.DataFrame(index=categorical_cols, columns=categorical_cols)

for col1 in categorical_cols:
    for col2 in categorical_cols:
        if col1 != col2:
            cramers_results.loc[col1, col2] = cramers_v(df_eda[col1], df_eda[col2])
        else:
            cramers_results.loc[col1, col2] = 1.0  # perfect correlation with itself

# Convert to float for heatmap
cramers_results = cramers_results.astype(float)

# Plot heatmap
plt.figure(figsize=(12,10))
sns.heatmap(cramers_results, annot=True, fmt=".2f", cmap="Blues")
plt.title("Cramér’s V Correlation Matrix (Categorical Features)")
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.show()
```




In this work, Cramér’s V was used to assess the strength of the relationship between categorical variables. Cramér’s V is derived from the chi-square statistic, and this provides a normalized measure that ranges from 0 to 1 (perfect correlation) (Skotarczak et al., 2019). The figure above indicates the heatmap visualizes Cramér’s V values between pairs of categorical variables. Moreover, darker tones indicate stronger relationships, while lighter tones indicate weaker or negligible relationships. For example, the Cramér’s V value between the variables EARFCN and PCI is 0.82, indicating a strong relationship between them. In detail, it can be said that the same or similar physical cell identities (PCIs) are often repeated for a given frequency band (EARFCN).

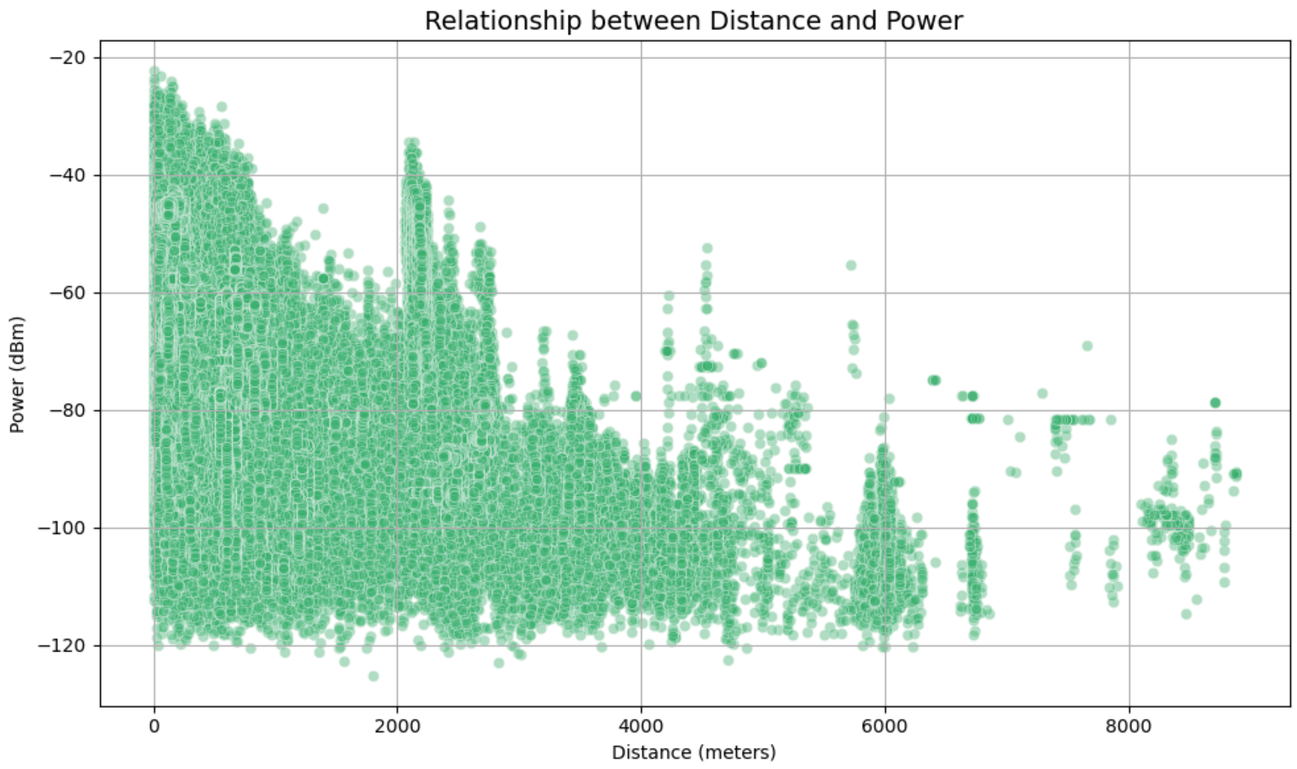
In [76]:
```python
# Extracting individual features for plotting
x = df_eda['RSRP']  # Reference Signal Received Power
y = df_eda['RSRQ']  # Reference Signal Received Quality
z = df_eda['Power']  # Power measurement

# Creating a 3D figure to visualize the relationship between RSRP, RSRQ, and Power
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')  # Defining a 3D axis for the plot

# Generating a 3D scatter plot with color intensity mapped to the 'Power' feature
sc = ax.scatter(x, y, z, c=z, cmap='viridis', s=50, alpha=0.7)

# Setting axis labels to specify the parameters being plotted
ax.set_xlabel('RSRP')  # X-axis represents received power strength
```

```
ax.set_ylabel('RSRQ')  # Y-axis represents received signal quality
ax.set_zlabel('Power')  # Z-axis represents power measurement
ax.set_title('3D Scatter Plot of RSRP, RSRQ, and Power')  # Title for clarity

# Adding a color bar to indicate intensity variations in the Power feature
cb = plt.colorbar(sc, ax=ax, shrink=0.5, aspect=10)  # Adjust size and aspect ratio
cb.set_label('Power Intensity')  # Label describing the significance of colors

# Display the visualization
plt.show()
```



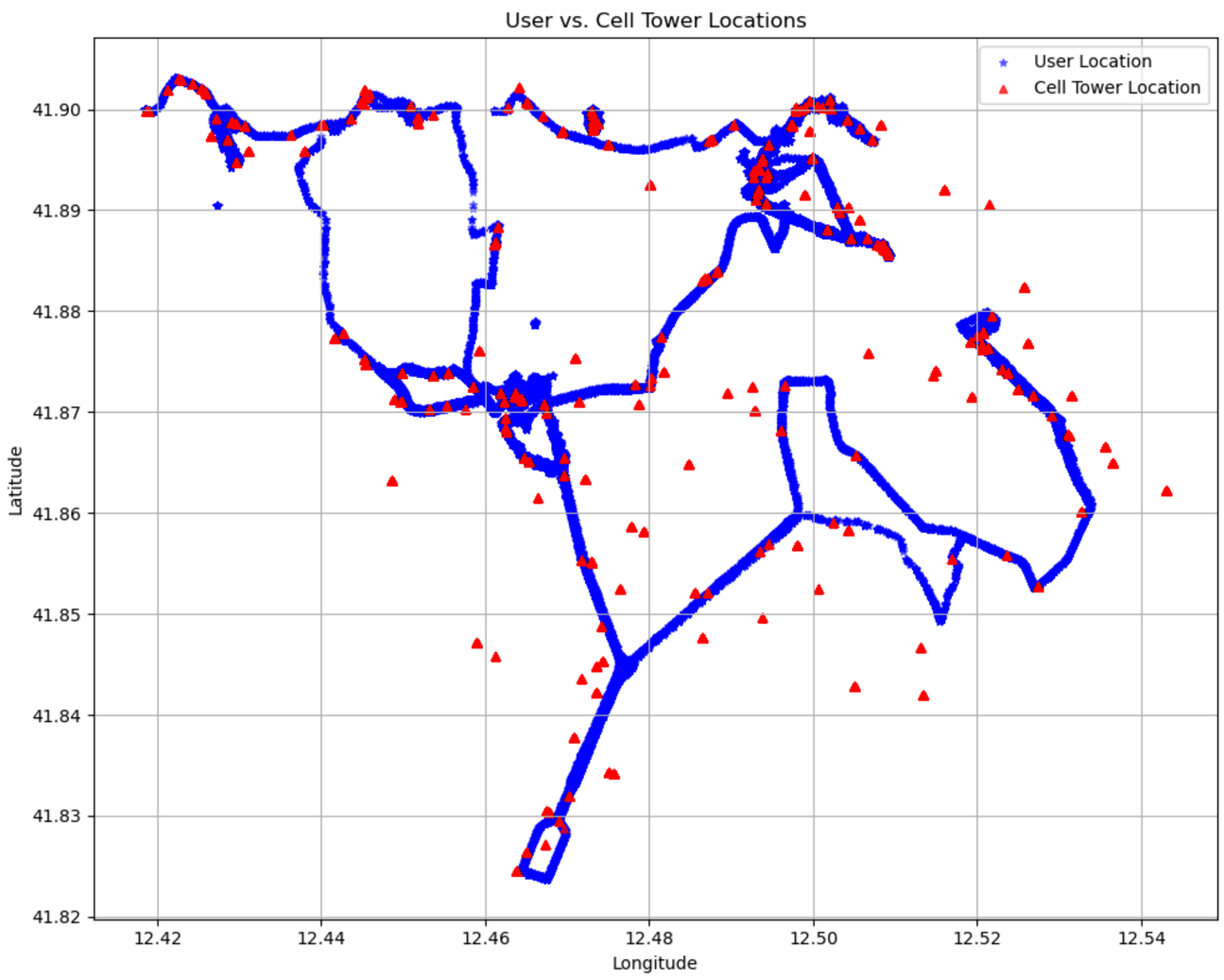

A 3D graph of the RSRP, RSRQ and Power columns was plotted as seen in figure given above. Each data point is color-coded according to its power density, with yellow indicating higher power levels and purple indicating lower levels. In detail, a clear positive trend is observed between RSRP and Power. This indicates that stronger signal strength is associated with better signal reception. Moreover, RSRQ shows a consistent pattern, indicating that signal quality improves with increasing power. The density and alignment of the points emphasize the non-random structure. Furthermore, this supports the assumption of a significant correlation between these features. This visualization is particularly useful for identifying patterns in signal performance and can assist in feature selection for modelling or clustering tasks.

In [78]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df_eda, x="distance", y="Power", alpha=0.4, color="mediumseagreen")

plt.title("Relationship between Distance and Power", fontsize=14)
plt.xlabel("Distance (meters)")
plt.ylabel("Power (dBm)")
plt.grid(True)
plt.tight_layout()
plt.show()
```



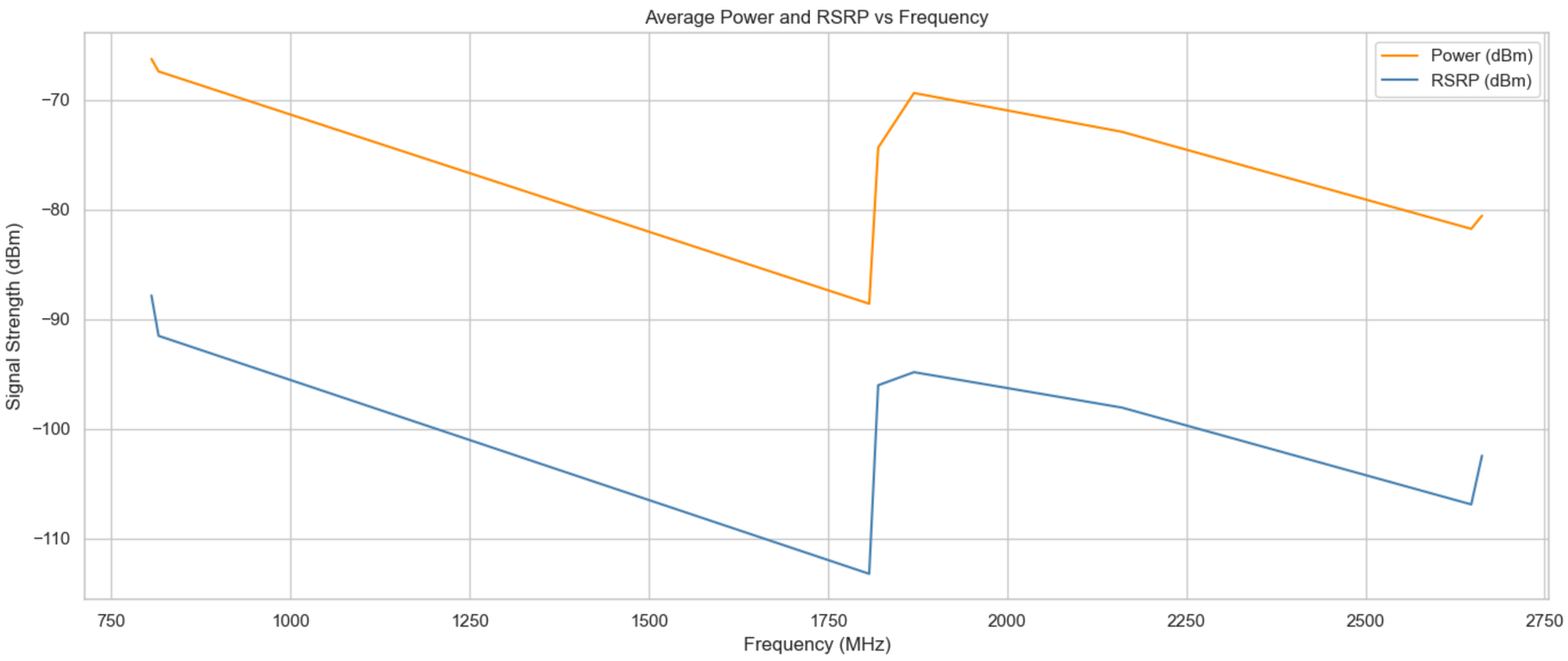

The scatter plot in figure given above shows the inverse relationship between signal strength and distance. As the distance from the source increases, the received power decreases continuously, highlighting the signal attenuation in space. This negative correlation reflects the common wireless communication behaviour where greater distances result in higher path loss, which in turn reduces signal strength.

In [80]:
```
plt.figure(figsize=(10, 8))

# User locations (marked with a star '*')
plt.scatter(df_eda['Longitude'], df_eda['Latitude'],
            s=20, c='blue', marker='*', label='User Location', alpha=0.5)

# Cell tower locations (marked with a triangle '^')
plt.scatter(df_eda['cellLongitude'], df_eda['cellLatitude'],
            s=20, c='red', marker='^', label='Cell Tower Location', alpha=0.7)

# Axis labels
plt.xlabel('Longitude')
plt.ylabel('Latitude')

# Title for better readability
plt.title('User vs. Cell Tower Locations')

# Legend for clarity
plt.legend()

# Grid for better visualization
plt.grid(True)

# Adjust layout for optimal spacing
plt.tight_layout()

# Show the plot
plt.show()
```



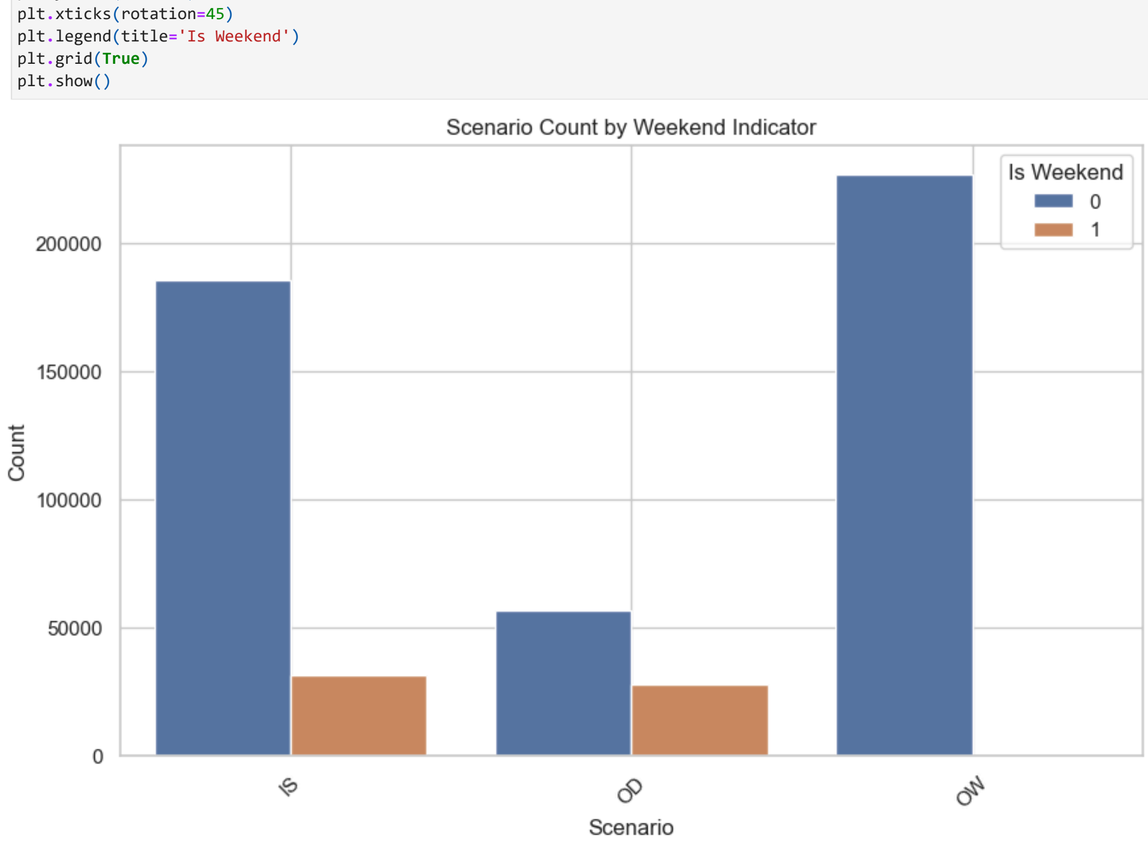

The correlation matrix revealed that there is a high correlation between Latitude, Longitude, cellLongitude and cellLatitude. The figure given above illustrates the locations of user locations and cell locations. This figure shows the location information as coordinates and reveals their locations.

In [82]:
```
# Grouping data by frequency and calculating the mean of Power and RSRP
grouped = df_eda.groupby('Frequency')[['Power', 'RSRP']].mean().reset_index()

# Set the plot style
sns.set(style="whitegrid")

# Plotting the line charts
plt.figure(figsize=(14, 6))

# Line chart for Power
sns.lineplot(data=grouped, x='Frequency', y='Power', label='Power (dBm)', color='darkorange')

# Line chart for RSRP
sns.lineplot(data=grouped, x='Frequency', y='RSRP', label='RSRP (dBm)', color='steelblue')

# Titles and labels
plt.title('Average Power and RSRP vs Frequency')
plt.xlabel('Frequency (MHz)')
plt.ylabel('Signal Strength (dBm)')
plt.legend()
plt.tight_layout()
plt.show()
```




The figure given above illustrates the relationship between average Power and RSRP across different frequency bands. As frequency increases, both Power and RSRP generally decrease. This indicates signal attenuation at higher frequencies. A sharp improvement is observed around 1800 MHz, likely due to optimized network configurations or favourable propagation characteristics within that band.

In [84]:
```
# Count plot to compare scenario distribution between weekdays and weekends
plt.figure(figsize=(10,6))
sns.countplot(data=df_eda, x='scenario', hue='is_weekend')
plt.title('Scenario Count by Weekend Indicator')
plt.xlabel('Scenario')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Is Weekend')
plt.grid(True)
plt.show()
```




The chart illustrates scenario counts split by weekday and weekend. All scenarios IS, OD, and OW occur more frequently on weekdays. OW shows the highest weekday activity, while OD has the most balanced distribution. This suggests reduced network activity during weekends across all scenarios.

In [86]:
```
del df_eda # delete df_eda dataframe after Explanatory Data Analysis finished
```

# 4. Clustering Analysis (Task 2)

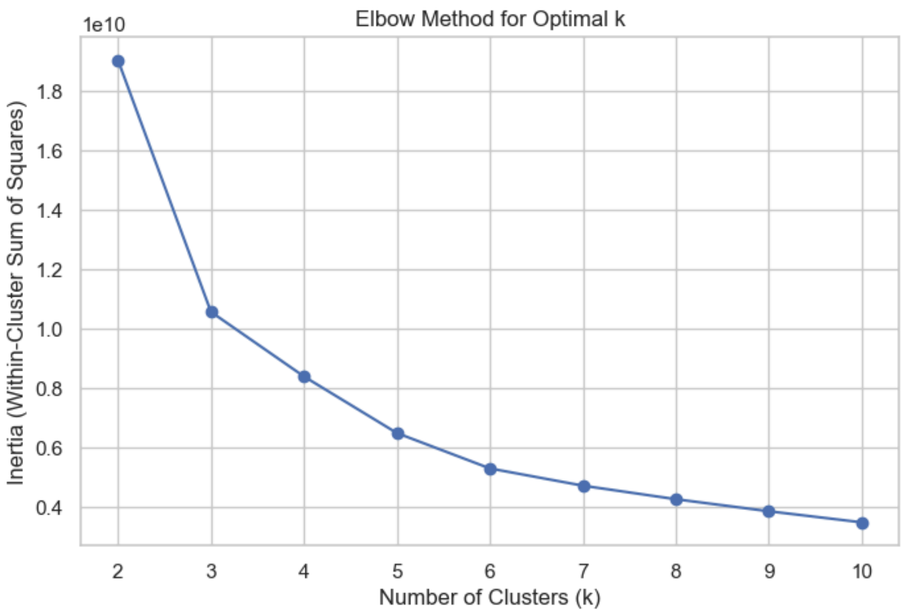
## 4.1. K-Means Clustering

In [89]:
```
df = df.sample(frac=0.05, random_state=42) # use 5% of data for only clustering
```

Considering the experimental setup, a random 5% portion of the dataset was taken only for clustering task in terms of time and processing power efficiency.

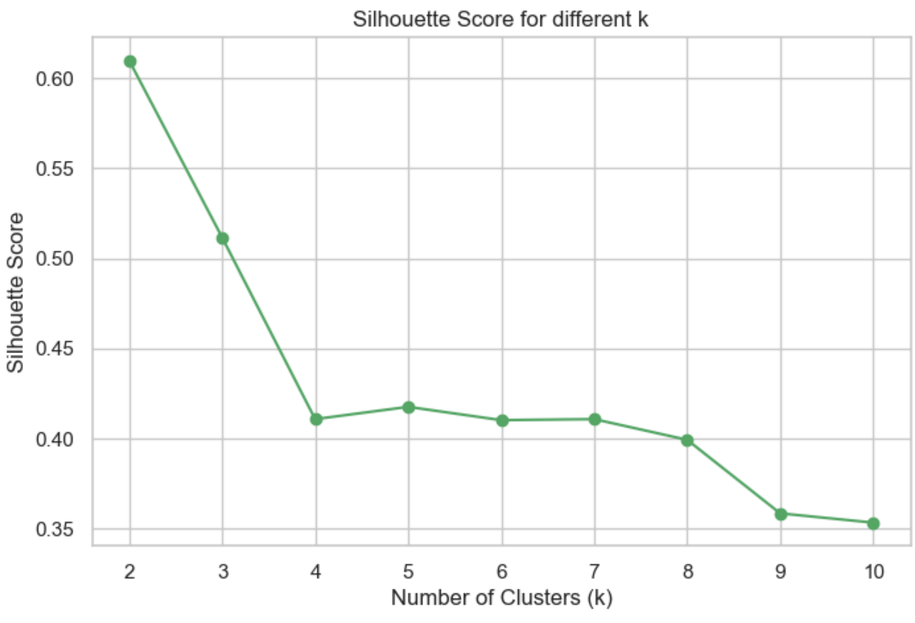
### K-Means with Using Encoded Catogorical Columns and Scaled Numerical Columns

In [92]:
```
# --- Prepare Dataframe ---
X = df[numeric_cols + categorical_cols ]  # In this part both numerical and categorical columns used for clustering

# --- Elbow Method to find optimal k ---
inertia = []
K = range(2, 11)

for k in K:
    kmeans = KMeans(
        n_clusters=k,
        init='k-means++',   # KMeans++ initialization
        n_init=10,
        max_iter=300,
        random_state=42
    )
    kmeans.fit(X)
    inertia.append(kmeans.inertia_)

# Plot Elbow Curve
plt.figure(figsize=(8, 5))
plt.plot(K, inertia, 'bo-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia (Within-Cluster Sum of Squares)')
plt.title('Elbow Method for Optimal k')
plt.grid(True)
plt.show()
```




In this study, normalized numeric data was used together with categorical variables encoded in the first K means algorithm. However, since the structure of categorical variables does not fit k-means, a noticeable performance loss was noticed. As seen in above, the cluster numbers and silhouette scores of K-means performed with all different data are seen. For this reason, the study was performed only with numerical data.

In [94]:
```
# --- Silhouette Scores for different k values ---
silhouette_scores = []
K = range(2, 11)

for k in K:
    kmeans = KMeans(n_clusters=k, init='k-means++', n_init=10, max_iter=300, random_state=42)
    labels = kmeans.fit_predict(X)
    score = silhouette_score(X, labels)
    silhouette_scores.append(score)

# Plot Silhouette Scores
plt.figure(figsize=(8, 5))
plt.plot(K, silhouette_scores, 'go-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Score for different k')
plt.grid(True)
plt.show()
```



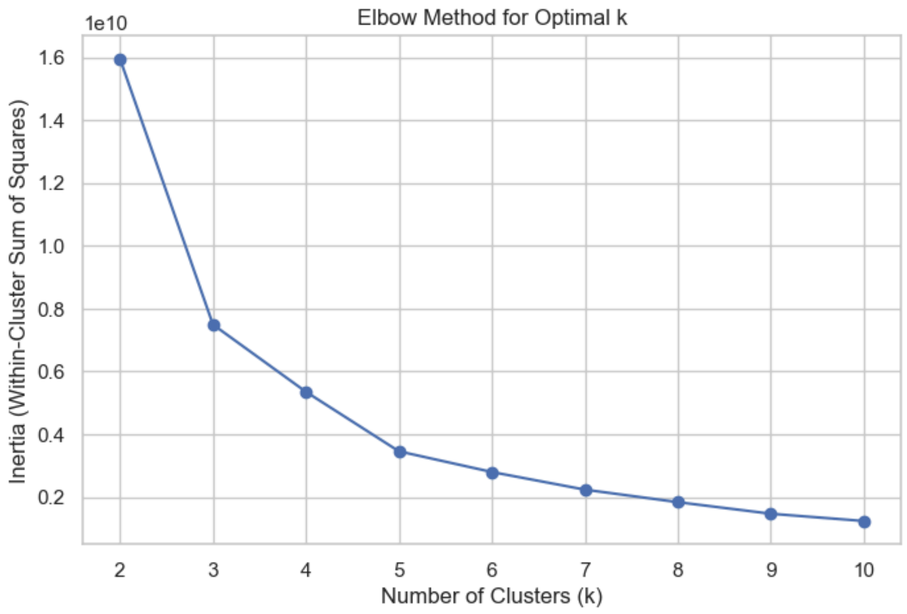

In [95]:
```
for k in K:
    print(f"Cluster Number: {k}, Silhouette Score: {silhouette_scores[k-2]:.2f}")
```

```
Cluster Number: 2, Silhouette Score: 0.61
Cluster Number: 3, Silhouette Score: 0.51
Cluster Number: 4, Silhouette Score: 0.41
Cluster Number: 5, Silhouette Score: 0.42
Cluster Number: 6, Silhouette Score: 0.41
Cluster Number: 7, Silhouette Score: 0.41
Cluster Number: 8, Silhouette Score: 0.40
Cluster Number: 9, Silhouette Score: 0.36
Cluster Number: 10, Silhouette Score: 0.35
```

### K-Means with Using Scaled Numerical Columns

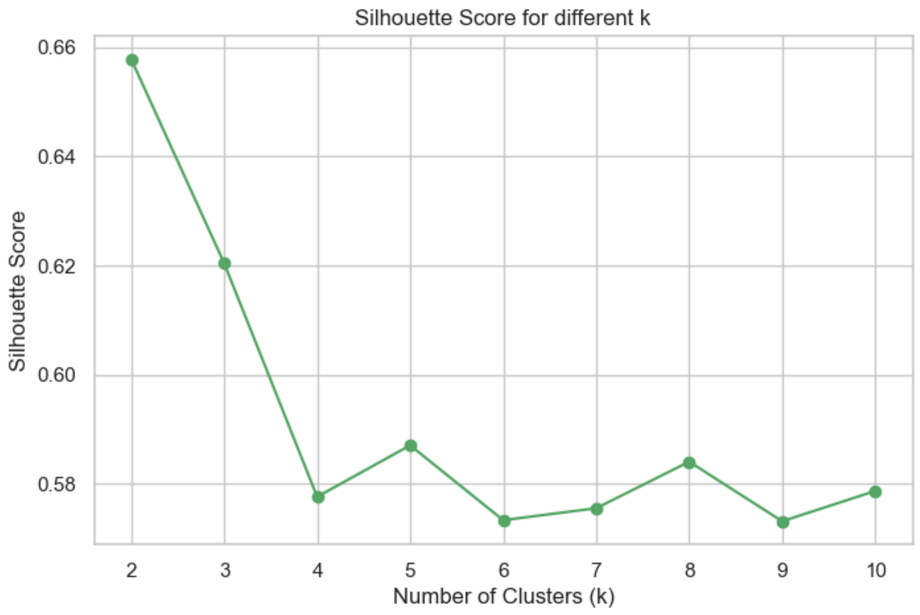
In [97]:
```
# --- Preprocessed DataFrame ---
X = df[numeric_cols]  # only numerical variables

# --- Elbow Method to find optimal k ---
inertia = []
K = range(2, 11)

for k in K:
    kmeans = KMeans(
        n_clusters=k,
        init='k-means++',   # KMeans++ initialization
        n_init=10,
        max_iter=300,
        random_state=42
    )
    kmeans.fit(X)
    inertia.append(kmeans.inertia_)

# Plot Elbow Curve
plt.figure(figsize=(8, 5))
plt.plot(K, inertia, 'bo-')
plt.xlabel('Number of Clusters (k)')
```

```
plt.ylabel('Inertia (Within-Cluster Sum of Squares)')
plt.title('Elbow Method for Optimal k')
plt.grid(True)
plt.show()
```




Based on the elbow method illustrated in plot above, the optimal number of clusters appears to be 3. At this point, there is a significant reduction in the within-cluster sum of squares (inertia), and the rate of decrease slows down beyond this value. In addition, as Shi et al. (2021) pointed this inflection point indicates a balance between model complexity and performance. Therefore, selecting three clusters is likely to provide meaningful separation without overfitting the data.

In [99]:
```
# --- Silhouette Scores for different k values ---
silhouette_scores = []
K = range(2, 11)
for k in K:
    kmeans = KMeans(n_clusters=k, init='k-means++', n_init=10, max_iter=300, random_state=42)
    labels = kmeans.fit_predict(X)
    score = silhouette_score(X, labels)
    silhouette_scores.append(score)

# Plot Silhouette Scores
plt.figure(figsize=(8, 5))
plt.plot(K, silhouette_scores, 'go-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Score for different k')
plt.grid(True)
plt.show()
```

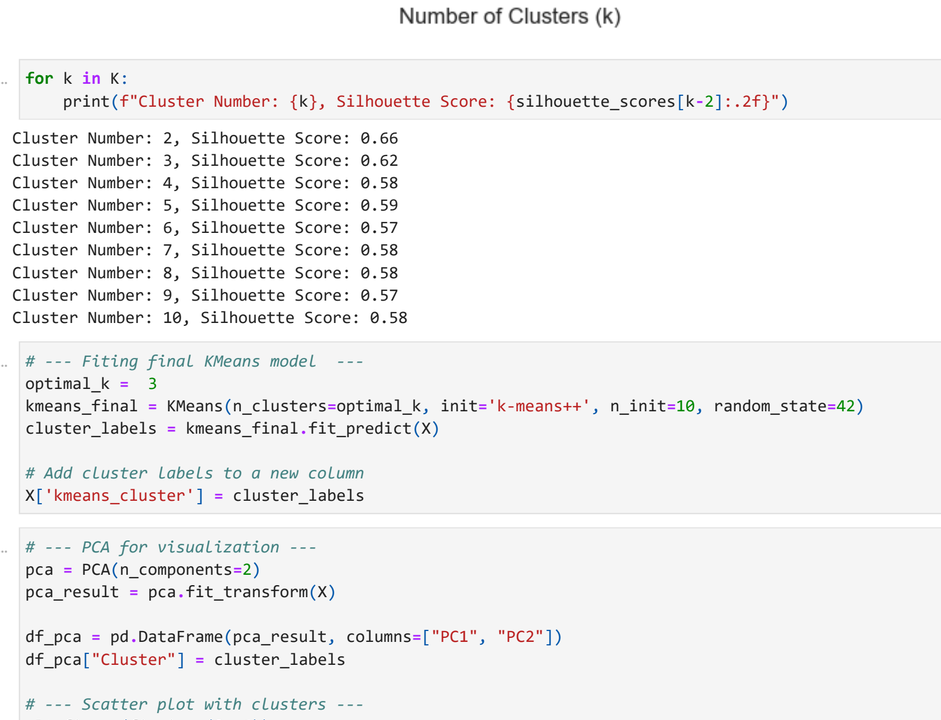



In [100…
```
for k in K:
    print(f"Cluster Number: {k}, Silhouette Score: {silhouette_scores[k-2]:.2f}")
```

```
Cluster Number: 2, Silhouette Score: 0.66
Cluster Number: 3, Silhouette Score: 0.62
Cluster Number: 4, Silhouette Score: 0.58
Cluster Number: 5, Silhouette Score: 0.59
Cluster Number: 6, Silhouette Score: 0.57
Cluster Number: 7, Silhouette Score: 0.58
Cluster Number: 8, Silhouette Score: 0.58
Cluster Number: 9, Silhouette Score: 0.57
Cluster Number: 10, Silhouette Score: 0.58
```

In [101…
```
# --- Fiting final KMeans model  ---
optimal_k =  3
kmeans_final = KMeans(n_clusters=optimal_k, init='k-means++', n_init=10, random_state=42)
cluster_labels = kmeans_final.fit_predict(X)

# Add cluster labels to a new column
X['kmeans_cluster'] = cluster_labels
```

In [102…
```
# --- PCA for visualization ---
pca = PCA(n_components=2)
pca_result = pca.fit_transform(X)

df_pca = pd.DataFrame(pca_result, columns=["PC1", "PC2"])
df_pca["Cluster"] = cluster_labels

# --- Scatter plot with clusters ---
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df_pca, x="PC1", y="PC2", hue="Cluster", palette="Set2", s=50)
plt.title("K-Means Clustering Visualized with PCA")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.legend(title="Cluster")
plt.grid(True)
plt.show()
```




The figure given above visualizes clustering using PCA, where data points are projected onto two principal components. The three clusters (0, 1, and 2) show clear separation, indicating that the algorithm successfully identified distinct groups in the dataset with minimal overlap.

In [104…
```
df['KMeans_Cluster'] = cluster_labels
```

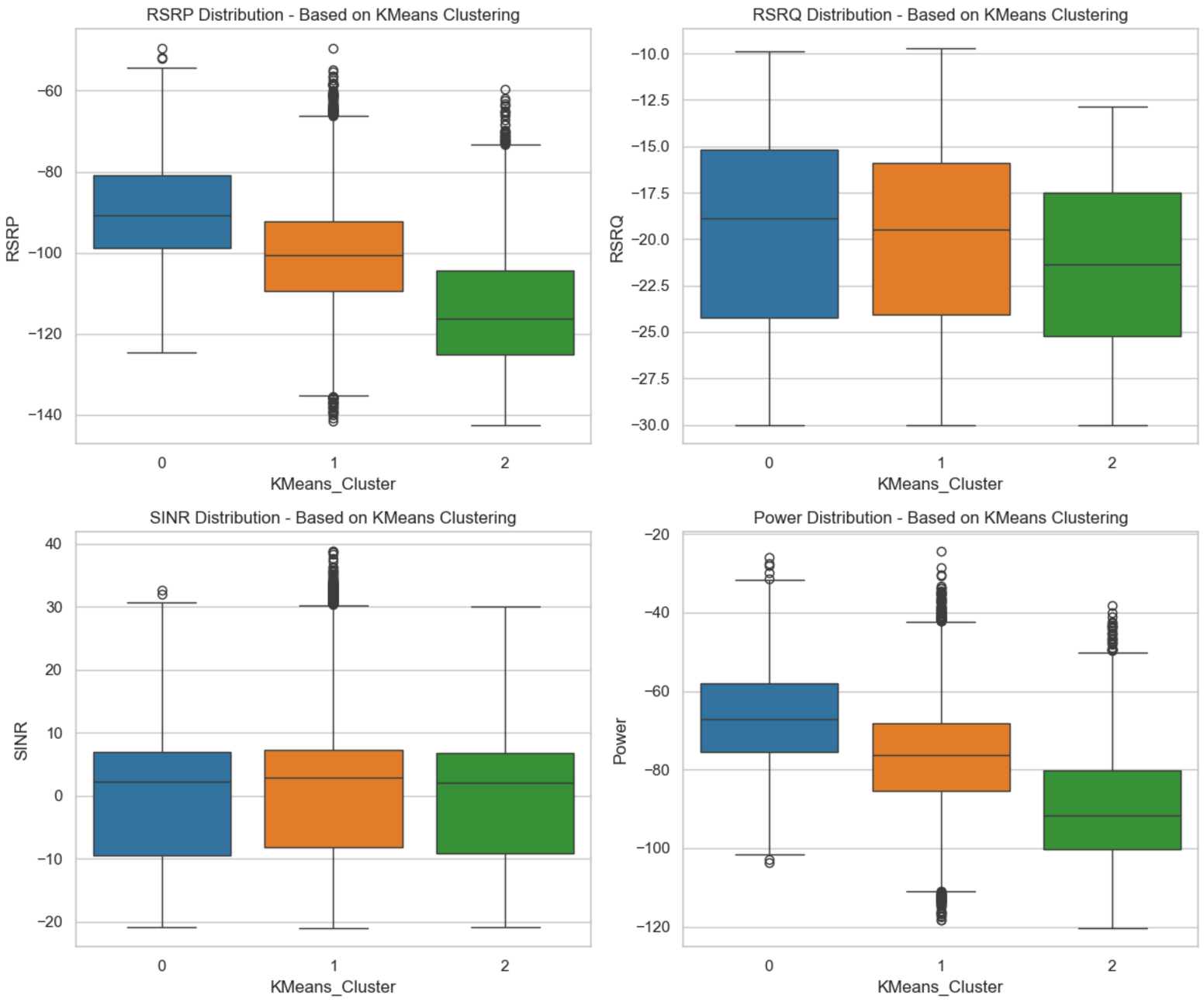
In [105…
```
df[numeric_cols + ["KMeans_Cluster"]].groupby('KMeans_Cluster').mean(numeric_only=True)
```

Out[105…

| KMeans_Cluster | Latitude | Longitude | Altitude | Speed | Frequency | Power | SINR | RSRP | RSRQ | cellLongitude | cellLatitude | cellPosErrorLambda1 | cellPosErrorLambda2 | n_CellIdentities | distance | Band | minute | hour | day | month | da |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 41.883420 | 12.486607 | 71.669401 | 5.123059 | 811.353012 | -66.693135 | -0.074406 | -89.616002 | -19.881291 | 12.487047 | 41.883997 | 6.978375 | 6.717572 | 7.958225 | 379.932160 | 20.000000 | 29.205938 | 12.641982 | 16.280338 | 7.824443 | |
| **1** | 41.884211 | 12.485864 | 70.664597 | 4.640890 | 2197.041954 | -76.539603 | 1.105606 | -100.592971 | -20.212311 | 12.486083 | 41.884663 | 14.948591 | 14.742572 | 7.613802 | 355.510260 | 3.993266 | 28.865647 | 12.823304 | 16.747024 | 8.133437 | |
| **2** | 41.877298 | 12.484683 | 65.488229 | 5.701742 | 1738.201682 | -89.018939 | -0.237862 | -113.266769 | -21.578011 | 12.485781 | 41.867788 | 10.040455 | 9.685056 | 7.413162 | 2942.785839 | 5.064325 | 28.875309 | 13.251361 | 15.586838 | 8.021277 | |

In [106…

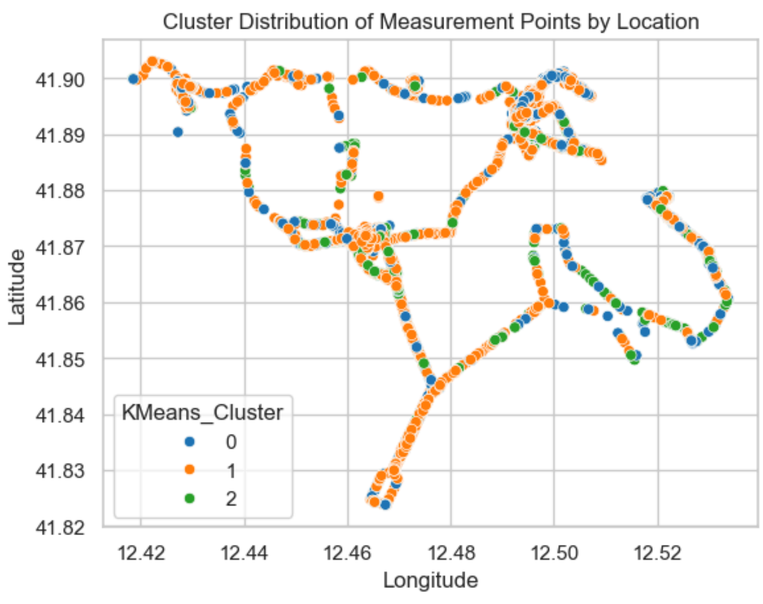
```
cluster_colors = ["#1f77b4", "#ff7f0e", "#2ca02c"]
fig, axes = plt.subplots(2, 2, figsize=(12, 10))  # Create  2x2 grid

# List of signal metrics to visualize
metrics = ['RSRP', 'RSRQ', 'SINR', 'Power']

# Loop through each metric and plot on respective subplot
for ax, col in zip(axes.flat, metrics):
    sns.boxplot(data=df, x='KMeans_Cluster', y=col, palette=cluster_colors, ax=ax)  # Apply custom colors
    ax.set_title(f"{col} Distribution - Based on KMeans Clustering")  # Set individual titles

plt.tight_layout()  # Adjust spacing for better visualization
plt.show()  # Display
```




The figure above shows the distribution of RSRP, RSRQ, SINR and Power across three clusters. Each subplot shows a clear variation in signal characteristics across clusters. It also highlights the effectiveness of the clustering approach in distinguishing patterns in the dataset. Cluster 2 consistently shows the poorest signal quality with the lowest median values for all four metrics, especially RSRP and Power, indicating poorer coverage. Besides, Cluster 0 appears to represent regions with better signal conditions reflected by higher median values. The clear separation in SINR and RSRQ values further supports the ability of the clustering model to segment data according to quality of service.

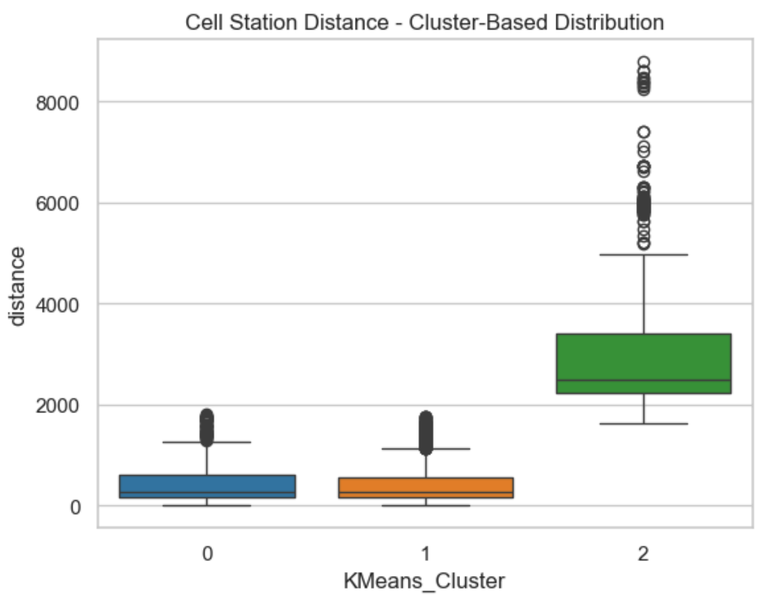
In [108…

```
# Scatter plot of measurement points based on geographic location
sns.scatterplot(data=df, x='Longitude', y='Latitude', hue='KMeans_Cluster', palette='tab10')

plt.title("Cluster Distribution of Measurement Points by Location")  # Set plot title
plt.show()  # Display the plot
```



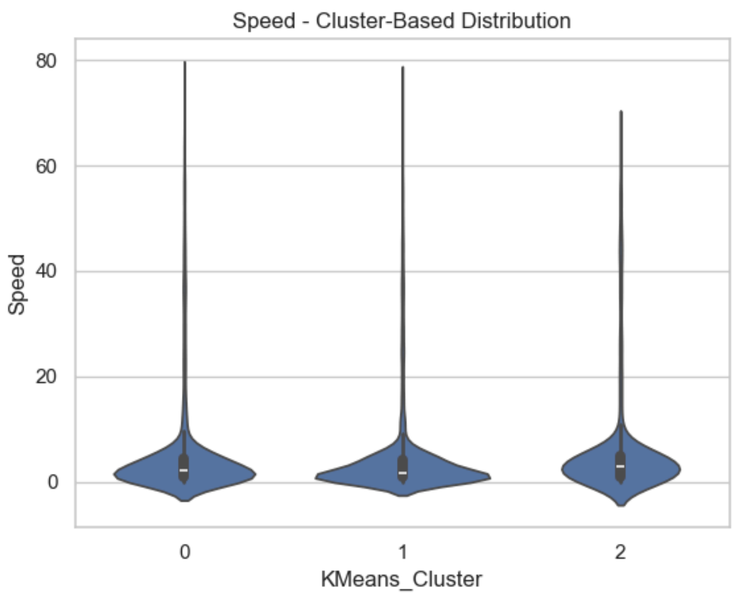

In [109…

```
cluster_colors = ["#1f77b4", "#ff7f0e", "#2ca02c"]  # Blue, Orange, Green

# Box plot showing base station distance distribution per cluster
sns.boxplot(data=df, x='KMeans_Cluster', y='distance', palette=cluster_colors)

plt.title("Cell Station Distance - Cluster-Based Distribution")  # Set plot title
plt.show()  # Display the plot
```

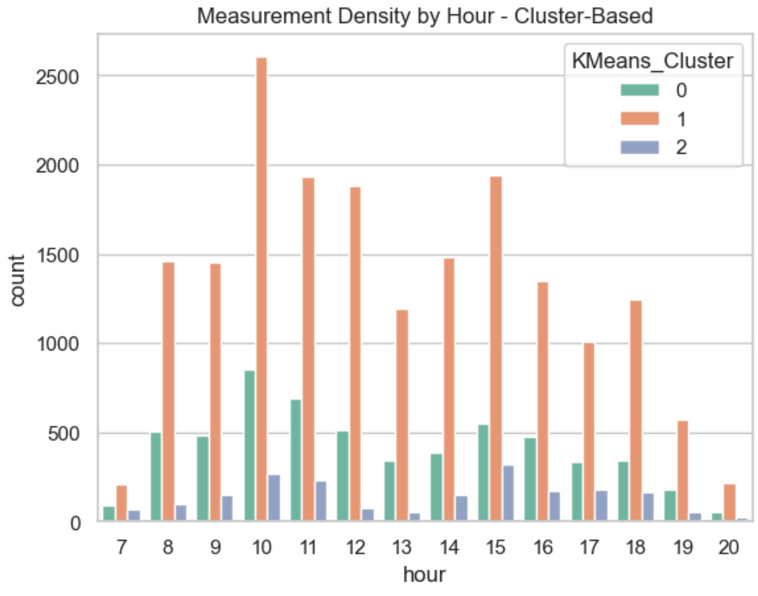



The plot above shows the distribution of cell location distances in the three clusters defined by K-Means clustering. Cluster 2 exhibits significantly higher distance values, including a wide range and a considerable number of outliers. It also shows that users in this cluster are generally farther from the cell location. In contrast, Clusters 0 and 1 have more compact distributions with lower median distances, indicating closer location to the cell station.

In [111…
```
# Violin plot showing speed distribution across KMeans clusters
sns.violinplot(data=df, x='KMeans_Cluster', y='Speed')

plt.title("Speed - Cluster-Based Distribution")  # Set plot title
plt.show()  # Display the plot
```

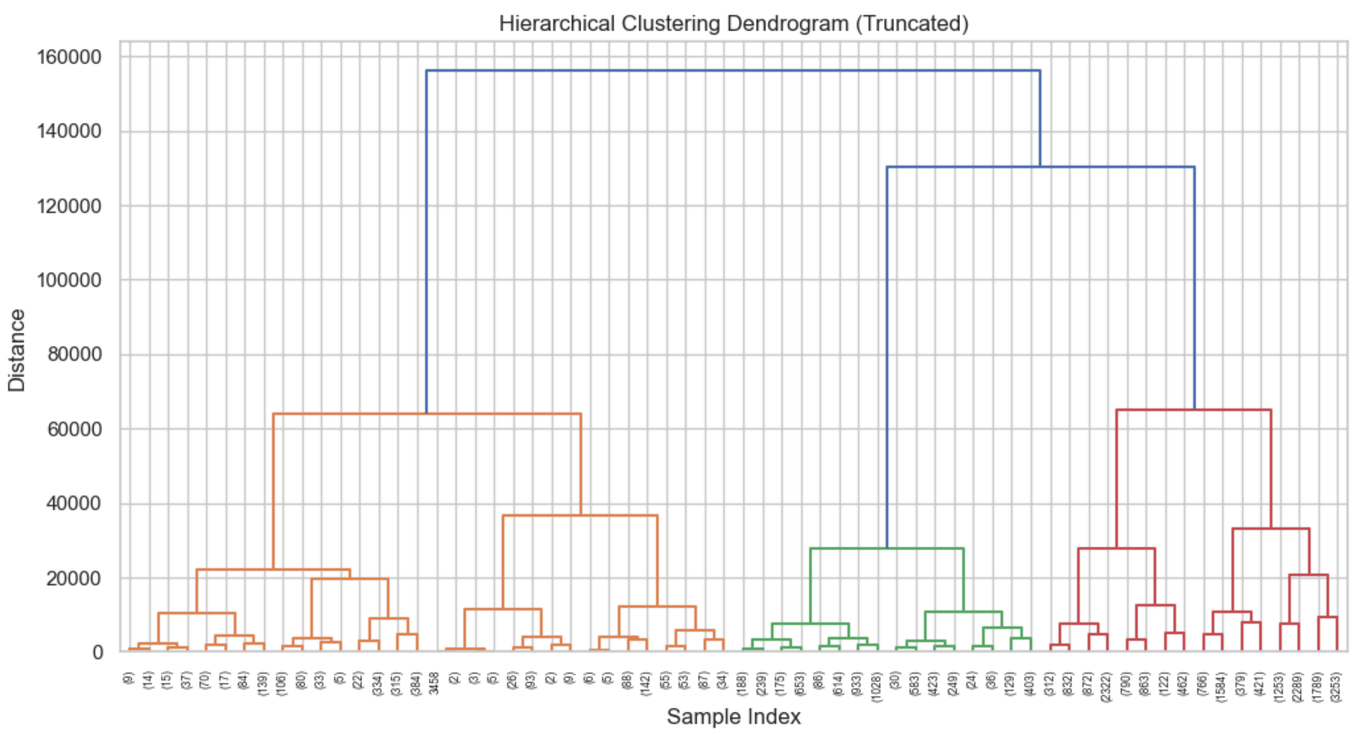



In [112…
```
# Count plot showing measurement density by hour and clustered with KMeans
sns.countplot(data=df, x='hour', hue='KMeans_Cluster', palette='Set2')

plt.title("Measurement Density by Hour - Cluster-Based")  # Set plot title
plt.show()  # Display the plot
```



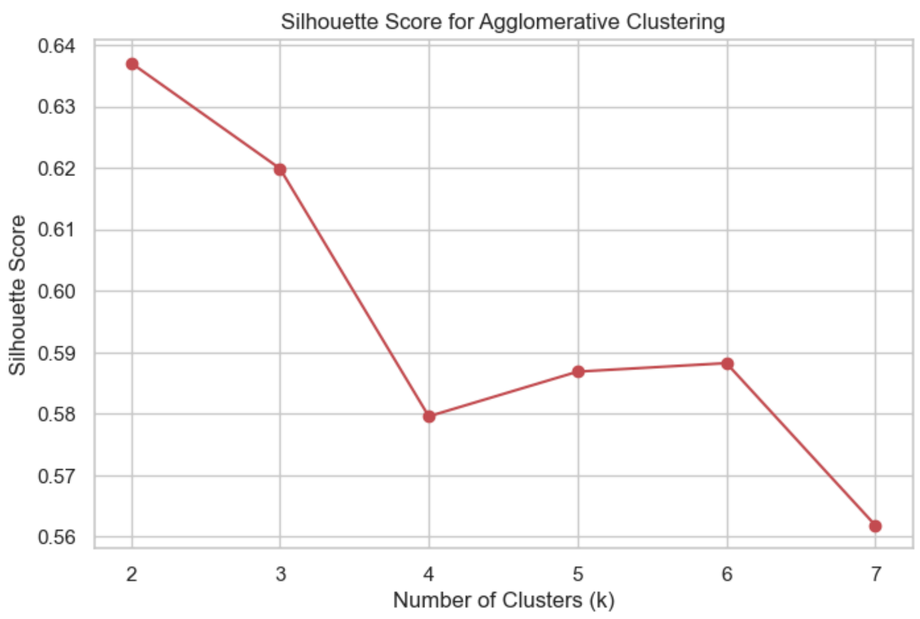

## 4.2. Agglomerative Clustering

In [114…
```
# --- Generate a Dendrogram using Ward linkage ---
linked = linkage(X, method='ward')  # Ward minimizes variance within clusters

plt.figure(figsize=(12, 6))
dendrogram(linked, truncate_mode='level', p=5)
plt.title('Hierarchical Clustering Dendrogram (Truncated)')
plt.xlabel('Sample Index')
plt.ylabel('Distance')
plt.show()
```




The figure above illustrates the hierarchical clustering dendrogram. This plot visually represents the nested grouping of data points according to their pairwise distances. In the figure, vertical lines indicate the distance at which clusters merge, and longer vertical lines reflect greater dissimilarity. Observe the largest vertical distances that are not crossed by horizontal lines, and a natural division into three main clusters is determined, represented by distinct colours. This visual gap, also known as the “distance threshold,” supports the selection of the optimal number of clusters without requiring prior assumptions (Li et al., 2022). Therefore, the dendrogram plays an important role for defining the optimal number of clusters in agglomerative clustering. So, the optimal number of clusters was determined as three. On the other hand, this is justified by the clear separation observed at a high linkage distance, where the data split into three main branches before large vertical mergers occur. This significant jump in linkage distance indicates a natural cutoff point.

In [116…
```
# --- Evaluate cluster quality using Silhouette Score ---
silhouette_scores = []
K = range(2, 8)

for k in K:
    model = AgglomerativeClustering(n_clusters=k)
    labels = model.fit_predict(X)
    score = silhouette_score(X, labels)
    silhouette_scores.append(score)

# Plot Silhouette Scores
plt.figure(figsize=(8,5))
plt.plot(K, silhouette_scores, 'ro-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.title('Silhouette Score for Agglomerative Clustering')
plt.grid(True)
plt.show()
```




In [117…
```
# --- Fit Agglomerative Model with Optimal k ---
optimal_k = 3  # based on silhouette and dendrogram
agg_model = AgglomerativeClustering(n_clusters=optimal_k)
agg_labels = agg_model.fit_predict(X)

# Add cluster labels to DataFrame
df['Agglo_Cluster'] = agg_labels
```

In [118…
```
# --- PCA + Cluster Visualization ---
pca = PCA(n_components=2)
pca_result = pca.fit_transform(X)

df_pca_agg = pd.DataFrame(pca_result, columns=["PC1", "PC2"])
df_pca_agg["Cluster"] = agg_labels

plt.figure(figsize=(8, 6))
sns.scatterplot(data=df_pca_agg, x="PC1", y="PC2", hue="Cluster", palette="Set2", s=50)
plt.title("Agglomerative Clustering Visualized with PCA")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.legend(title="Cluster")
plt.grid(True)
plt.show()
```

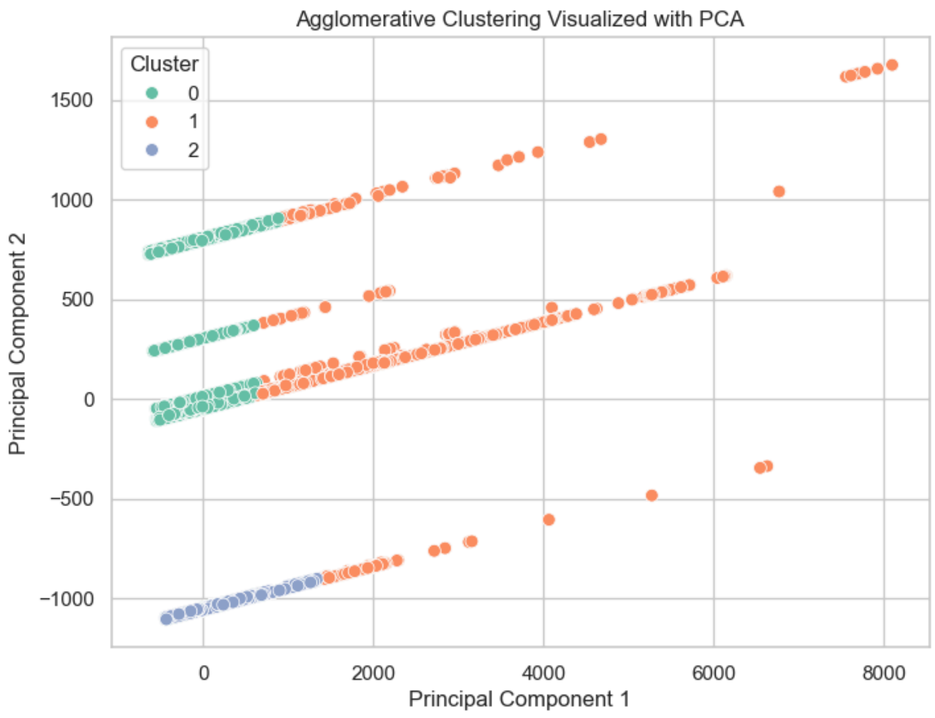


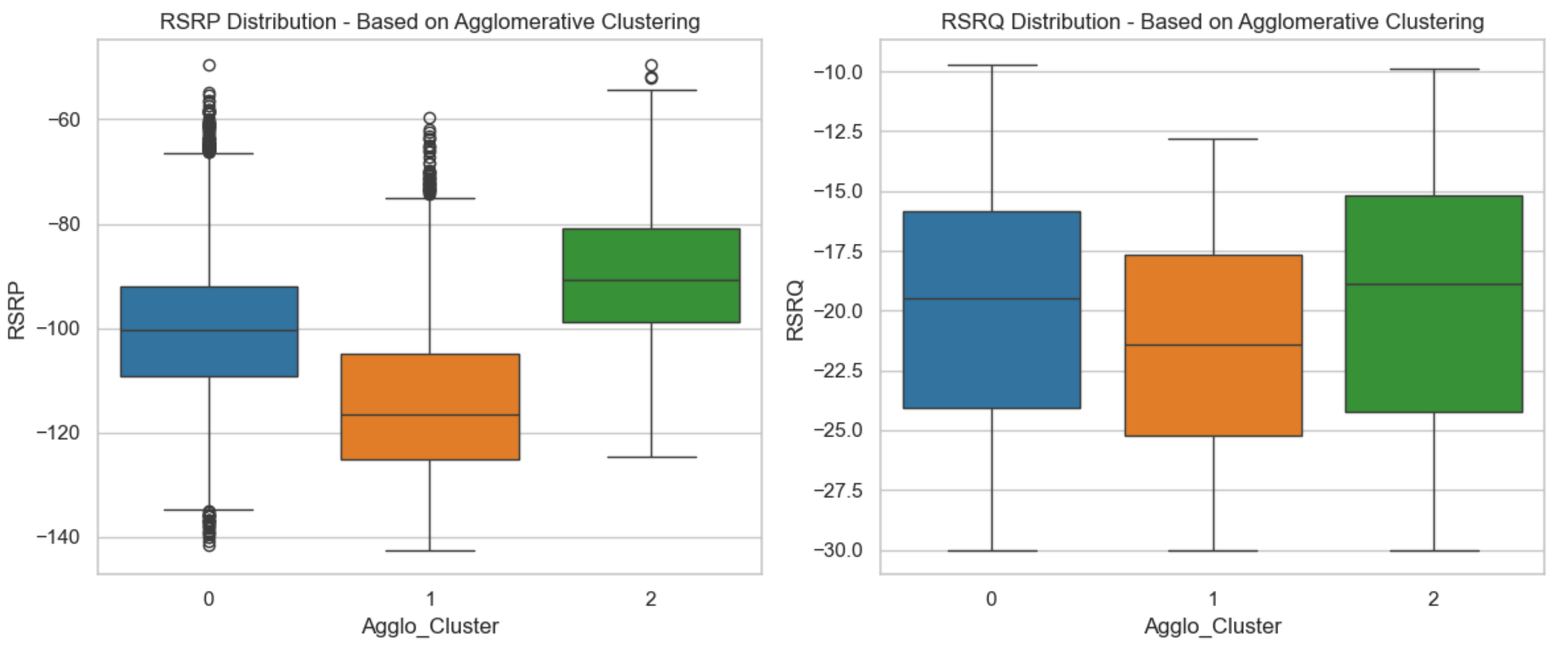

Figure given above visualizes clustering using PCA, where data points are projected onto two principal components. The three clusters (0, 1, and 2) show clear separation, indicating that the algorithm successfully identified distinct groups in the dataset with minimal overlap.

In [120…
```
df[numeric_cols + ["Agglo_Cluster"]].groupby('Agglo_Cluster').mean(numeric_only=True)
```

Out[120…

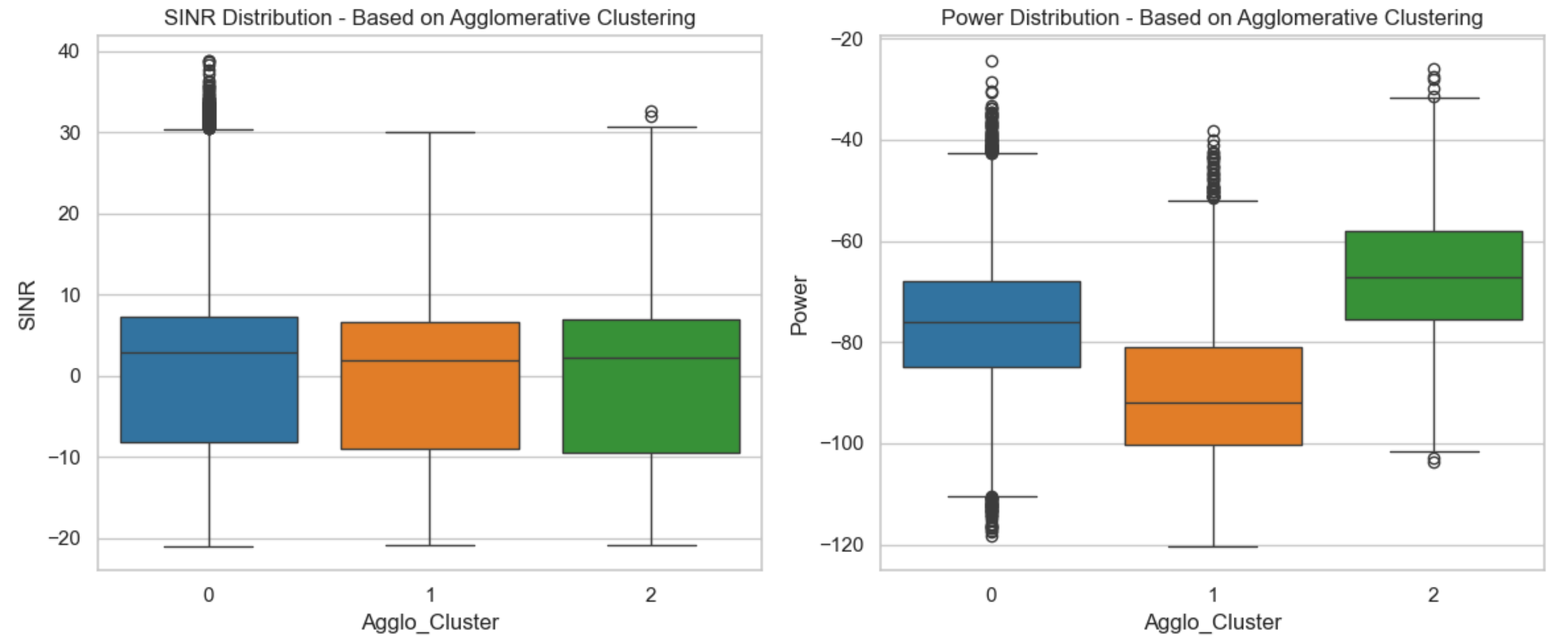
| Agglo_Cluster | Latitude | Longitude | Altitude | Speed | Frequency | Power | SINR | RSRP | RSRQ | cellLongitude | cellLatitude | cellPosErrorLambda1 | cellPosErrorLambda2 | n_CellIdentities | distance | Band | minute | hour | day | month | day |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 41.884341 | 12.485904 | 70.847572 | 4.552269 | 2201.225561 | -76.306456 | 1.137122 | -100.353045 | -20.184416 | 12.486181 | 41.884865 | 14.860776 | 14.655381 | 7.629636 | 341.193415 | 4.003550 | 28.909334 | 12.802119 | 16.738107 | 8.142280 | |
| **1** | 41.877022 | 12.484494 | 64.593596 | 6.296519 | 1755.761143 | -89.501985 | -0.341501 | -113.782659 | -21.650026 | 12.485021 | 41.868048 | 11.295161 | 10.951425 | 7.308132 | 2769.141494 | 4.861978 | 28.522637 | 13.374066 | 15.788132 | 7.962637 | |
| **2** | 41.883420 | 12.486607 | 71.669401 | 5.123059 | 811.353012 | -66.693135 | -0.074406 | -89.616002 | -19.881291 | 12.487047 | 41.883997 | 6.978375 | 6.717572 | 7.958225 | 379.932160 | 20.000000 | 29.205938 | 12.641982 | 16.280338 | 7.824443 | |

In [121…
```
cluster_colors = ["#1f77b4", "#ff7f0e", "#2ca02c"]
fig, axes = plt.subplots(2, 2, figsize=(12, 10))  # Create a 2x2 grid

# List of signal metrics to visualize
metrics = ['RSRP', 'RSRQ', 'SINR', 'Power']

# Loop through each metric and plot on respective subplot
for ax, col in zip(axes.flat, metrics):
    sns.boxplot(data=df, x='Agglo_Cluster', y=col, palette=cluster_colors, ax=ax)  # Apply custom colors
    ax.set_title(f"{col} Distribution - Based on Agglomerative Clustering")  # Set individual titles

plt.tight_layout()  # Adjust spacing for better visualization
plt.show()  # Display the plots
```









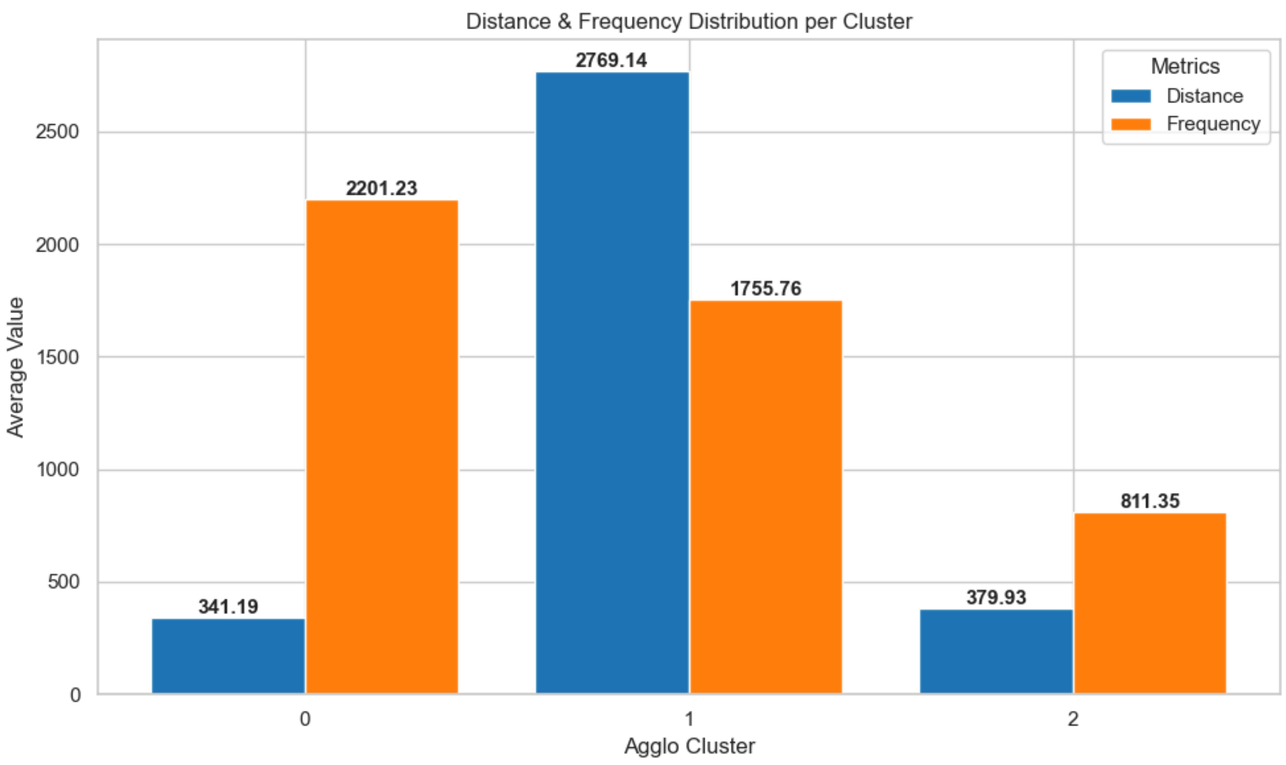




Plots given above indicate the distribution of RSRP, RSRQ, SINR, and Power across three clusters derived from agglomerative clustering. Each subplot reveals distinct variations in signal characteristics among the clusters. Cluster 1 exhibits the weakest signal conditions, marked by the lowest median values in RSRP and Power. Moreover, Cluster 2 demonstrates stronger signal characteristics with higher median values. The separation in RSRQ and SINR across the clusters further confirms the clustering model's capacity to differentiate data based on performance.

In [123…

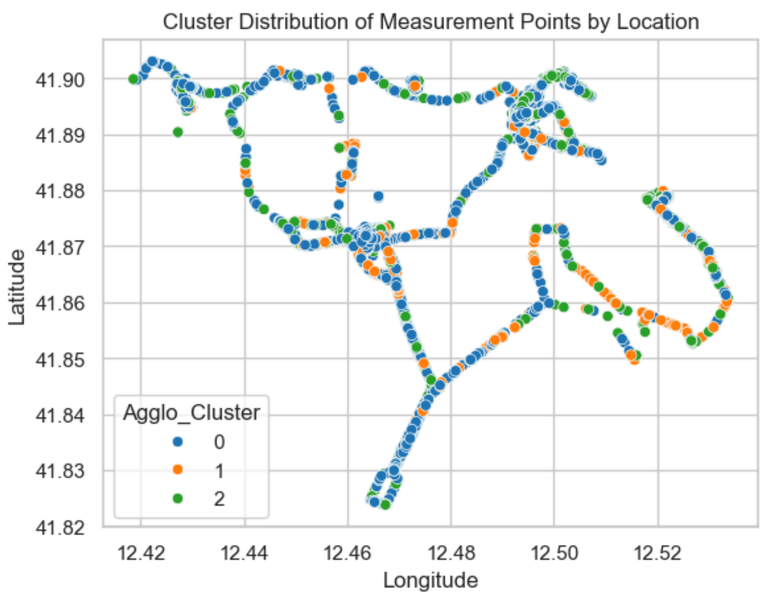
```python
# Calculate mean values for Distance and Frequency per cluster
cluster_means = df.groupby("Agglo_Cluster")[["distance", "Frequency"]].mean().reset_index()

# Define custom color palette
cluster_colors = ["#1f77b4", "#ff7f0e"]  # Blue for Distance, Orange for Frequency

# Create bar plot
fig, ax = plt.subplots(figsize=(10, 6))

# Set width for bars
bar_width = 0.4
x = np.arange(len(cluster_means["Agglo_Cluster"]))  # X positions

# Plot Distance bars
ax.bar(x - bar_width/2, cluster_means["distance"], width=bar_width, label="Distance", color=cluster_colors[0])

# Plot Frequency bars
ax.bar(x + bar_width/2, cluster_means["Frequency"], width=bar_width, label="Frequency", color=cluster_colors[1])

# Add labels on top of bars
for i in range(len(cluster_means)):
    ax.text(x[i] - bar_width/2, cluster_means["distance"][i], f"{cluster_means['distance'][i]:.2f}", ha='center', va='bottom', fontsize=11, fontweight="bold")
    ax.text(x[i] + bar_width/2, cluster_means["Frequency"][i], f"{cluster_means['Frequency'][i]:.2f}", ha='center', va='bottom', fontsize=11, fontweight="bold")

# Set labels and title
ax.set_xticks(x)
ax.set_xticklabels(cluster_means["Agglo_Cluster"])  # Cluster labels
ax.set_xlabel("Agglo Cluster")
ax.set_ylabel("Average Value")
ax.set_title("Distance & Frequency Distribution per Cluster")
ax.legend(title="Metrics")  # Add legend

plt.tight_layout()  # Adjust layout
plt.show()  # Display the plot
```




Plot given above illustrates the average values of Distance and Frequency in the three clusters. Cluster 1 stands out with the highest average distance (2769.14 meters), indicating that it represents data points located further away from the measurement source or cell towers. In contrast, Cluster 0 is characterized by the highest average frequency (2201.23 MHz) but the lowest distance (341.19 meters). Cluster 2 shows relatively balanced values with moderate averages in both metrics. These differences support the idea that clustering effectively captures the different spatial and spectral utilization patterns in the dataset.

In [125…

```python
# Scatter plot of measurement points based on geographic location
sns.scatterplot(data=df, x='Longitude', y='Latitude', hue='Agglo_Cluster', palette='tab10')

plt.title("Cluster Distribution of Measurement Points by Location")  # Set plot title
plt.show()  # Display the plot
```



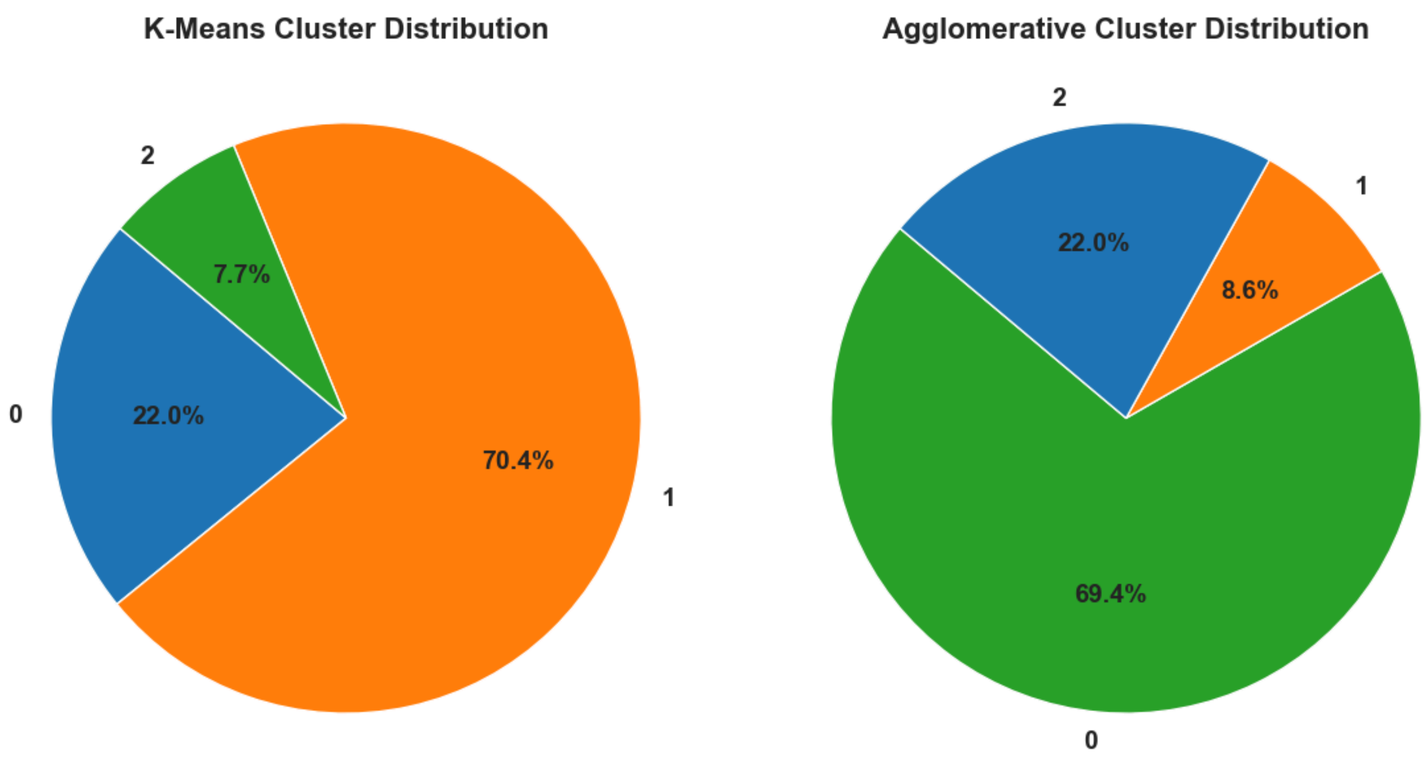

## 4.3 Clustering Models' Comparison

In [127…
```
df[numeric_cols + ["Agglo_Cluster", "KMeans_Cluster"]].groupby(['Agglo_Cluster', 'KMeans_Cluster']).mean(numeric_only=True)
```

Out[127…

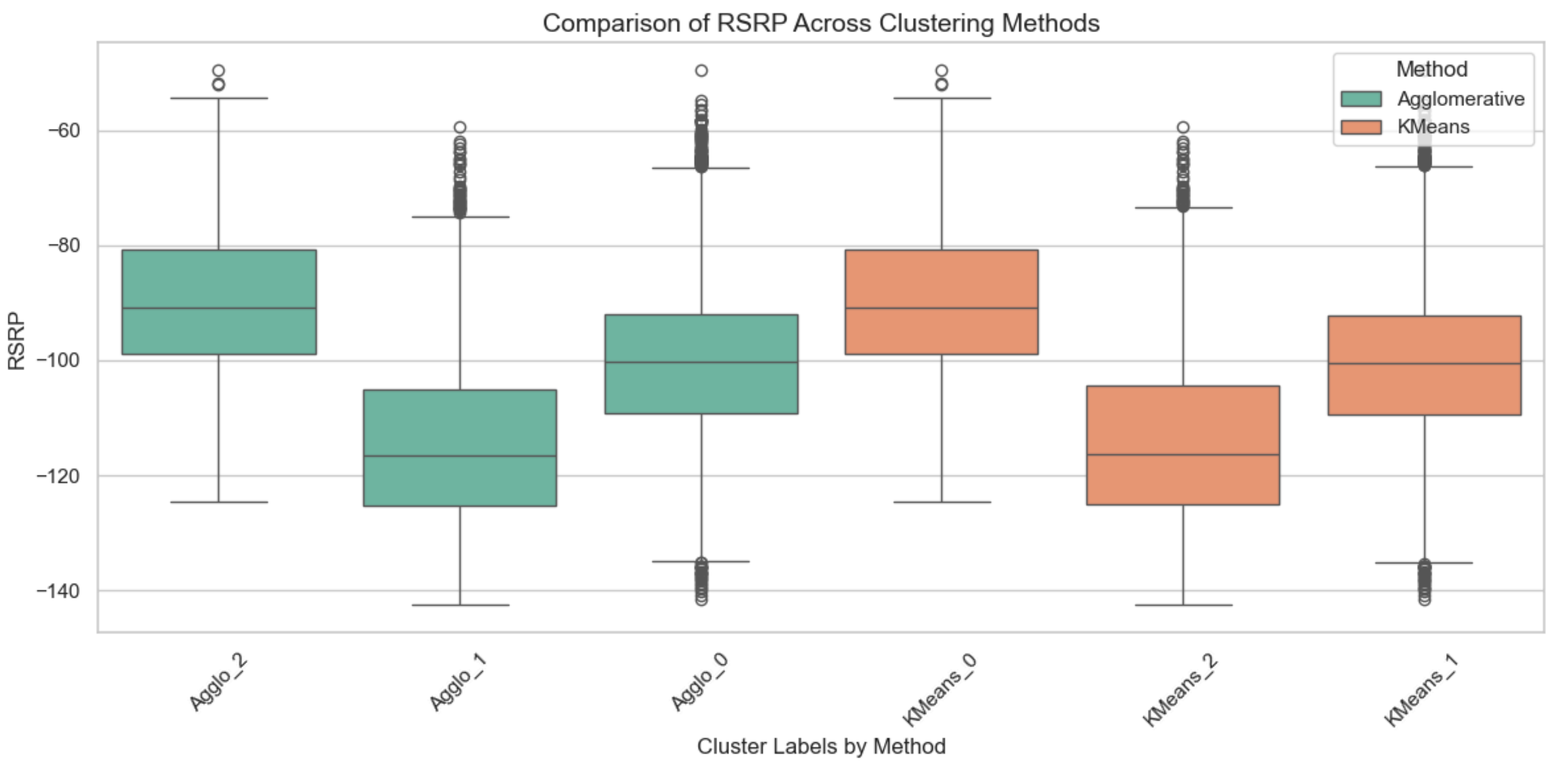
| Agglo_Cluster | KMeans_Cluster | Latitude | Longitude | Altitude | Speed | Frequency | Power | SINR | RSRP | RSRQ | cellLongitude | cellLatitude | cellPosErrorLambda1 | cellPosErrorLambda2 | n_CellIdentities | distance | Band | minute | hour | c |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | **1** | 41.884341 | 12.485904 | 70.847572 | 4.552269 | 2201.225561 | -76.306456 | 1.137122 | -100.353045 | -20.184416 | 12.486181 | 41.884865 | 14.860776 | 14.655381 | 7.629636 | 341.193415 | 4.003550 | 28.909334 | 12.802119 | 16.7381 |
| **1** | **1** | 41.874821 | 12.482992 | 57.475276 | 11.028976 | 1895.476378 | -93.345433 | -1.166122 | -117.887441 | -22.223031 | 12.478979 | 41.870120 | 21.278473 | 21.027530 | 6.472441 | 1387.506766 | 3.251969 | 25.716535 | 14.350394 | 17.3897 |
| | **2** | 41.877298 | 12.484683 | 65.488229 | 5.701742 | 1738.201682 | -89.018939 | -0.237862 | -113.266769 | -21.578011 | 12.485781 | 41.867788 | 10.040455 | 9.685056 | 7.413162 | 2942.785839 | 5.064325 | 28.875309 | 13.251361 | 15.5868 |
| **2** | **0** | 41.883420 | 12.486607 | 71.669401 | 5.123059 | 811.353012 | -66.693135 | -0.074406 | -89.616002 | -19.881291 | 12.487047 | 41.883997 | 6.978375 | 6.717572 | 7.958225 | 379.932160 | 20.000000 | 29.205938 | 12.641982 | 16.2803 |

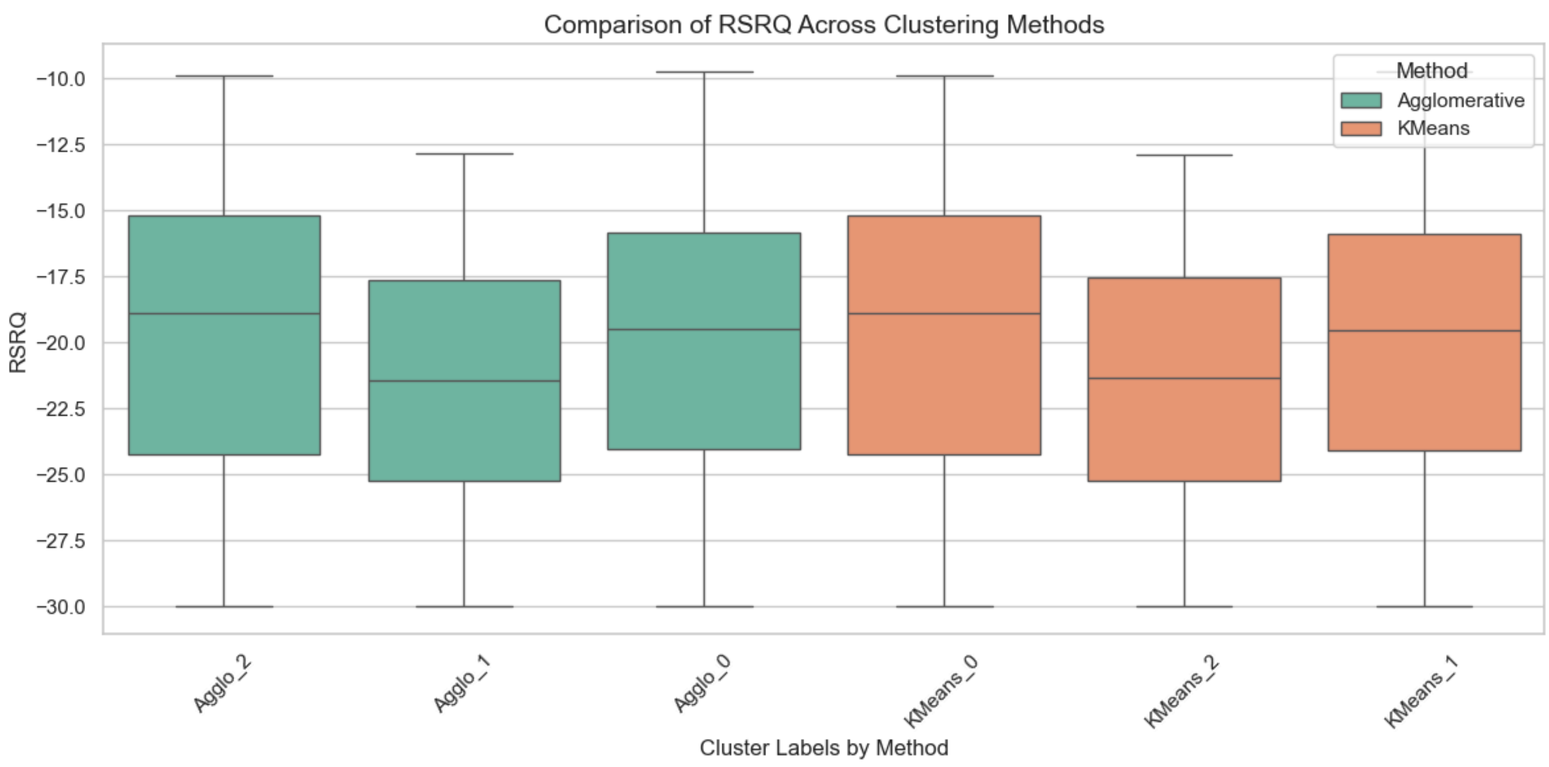
In [128…
```
# Count the number of occurrences for each cluster in K-Means and Agglomerative clustering
kmeans_counts = pd.Series(cluster_labels).value_counts().sort_index()
agglo_counts = pd.Series(agg_labels).value_counts().sort_index()

# Define color palettes for clusters to ensure visual differentiation
kmeans_colors = ["#1f77b4", "#ff7f0e", "#2ca02c"]  # Blue, orange, and green for K-Means
agglo_colors = ["#2ca02c", "#ff7f0e", "#1f77b4"]  # Green, orange, and blue for Agglomerative

# Create a figure with two subplots to visually compare cluster distributions
fig, axes = plt.subplots(1, 2, figsize=(12, 6))  # Two plots in one row for easy side-by-side comparison

# Plot the pie chart for K-Means clustering distribution
axes[0].pie(kmeans_counts, labels=kmeans_counts.index, autopct=lambda p: f"{p:.1f}%",
            colors=kmeans_colors, startangle=140, textprops={'fontsize': 14, 'fontweight': 'bold'})
axes[0].set_title("K-Means Cluster Distribution", fontsize=16, fontweight="bold")  # Set the title for better readability

# Plot the pie chart for Agglomerative clustering distribution
axes[1].pie(agglo_counts, labels=agglo_counts.index, autopct=lambda p: f"{p:.1f}%",
            colors=agglo_colors, startangle=140, textprops={'fontsize': 14, 'fontweight': 'bold'})
axes[1].set_title("Agglomerative Cluster Distribution", fontsize=16, fontweight="bold")  # Consistent title formatting

# Adjust layout to ensure plots don't overlap and have proper spacing
plt.tight_layout()

# Show the plots
plt.show()
```

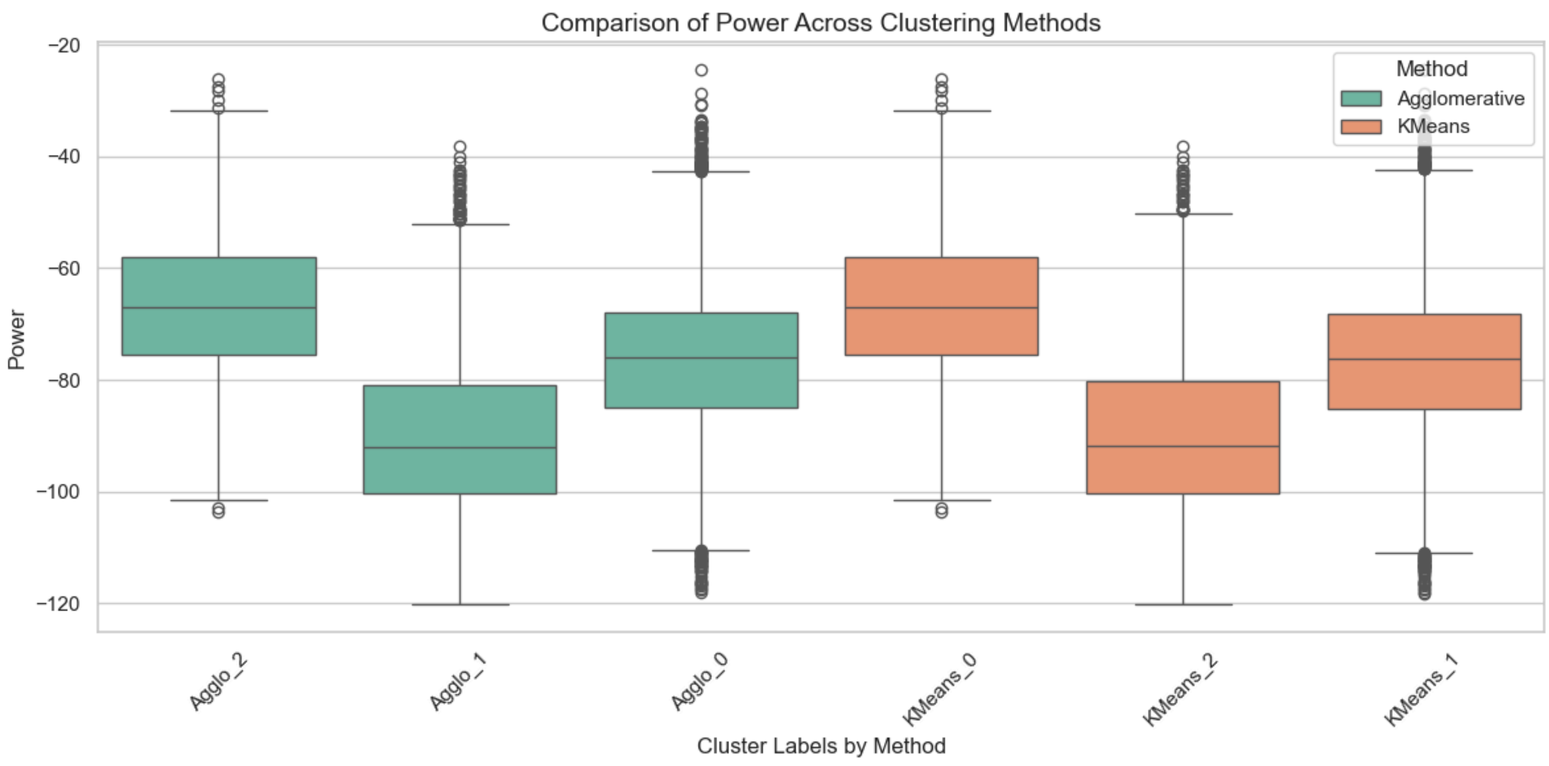


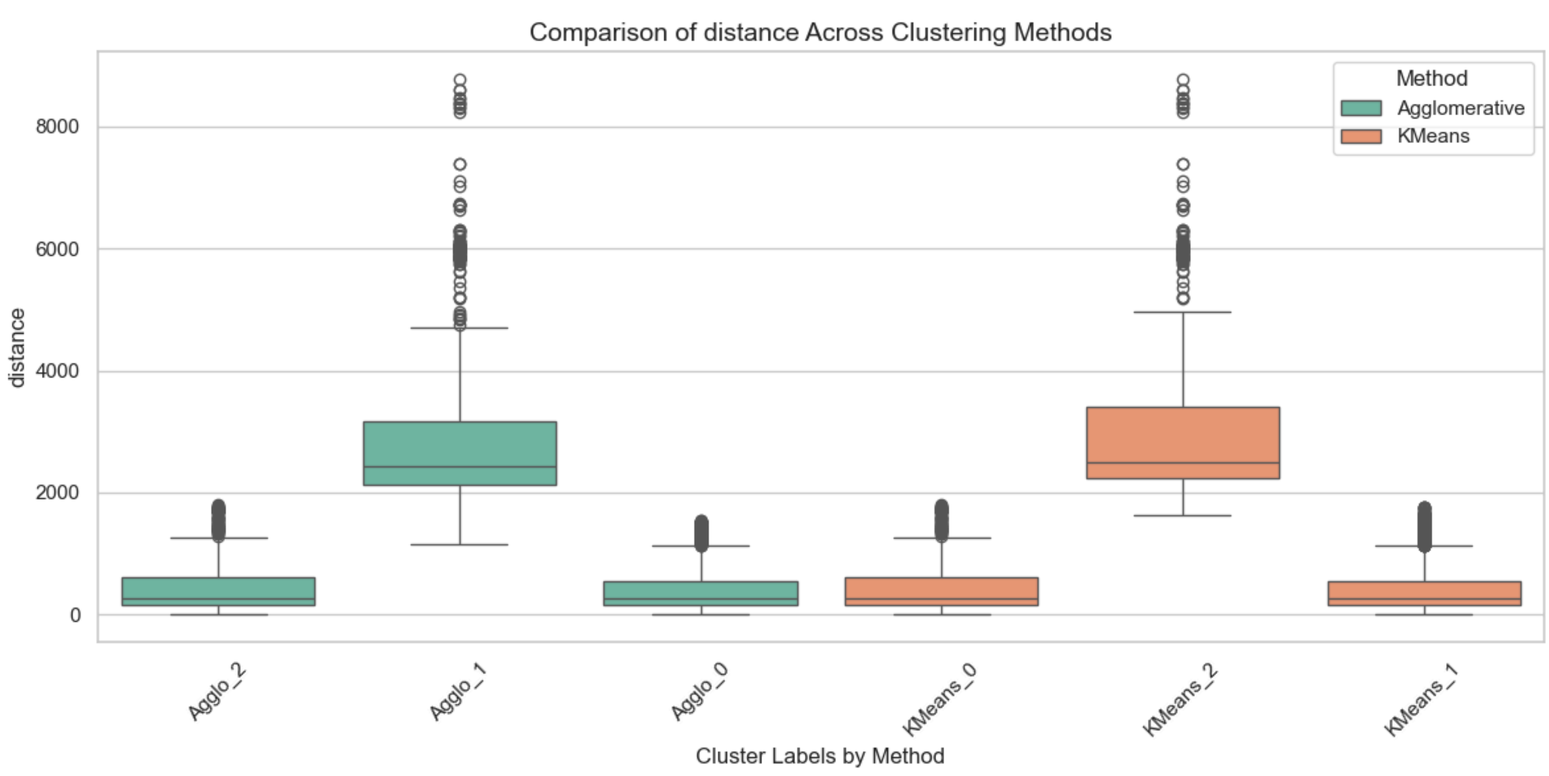

The pie charts given above illustrates a comparison of cluster sizes generated by the K-Means and Agglomerative algorithms. Although both methods include 3 clusters, the distribution of data points across clusters differs significantly. For instance, K-Means generated a dominant cluster at label 1, while Agglomerative clustering concentrated more points at label 0. Moreover, the Silhouette Scores for both clustering methods are 0.62.

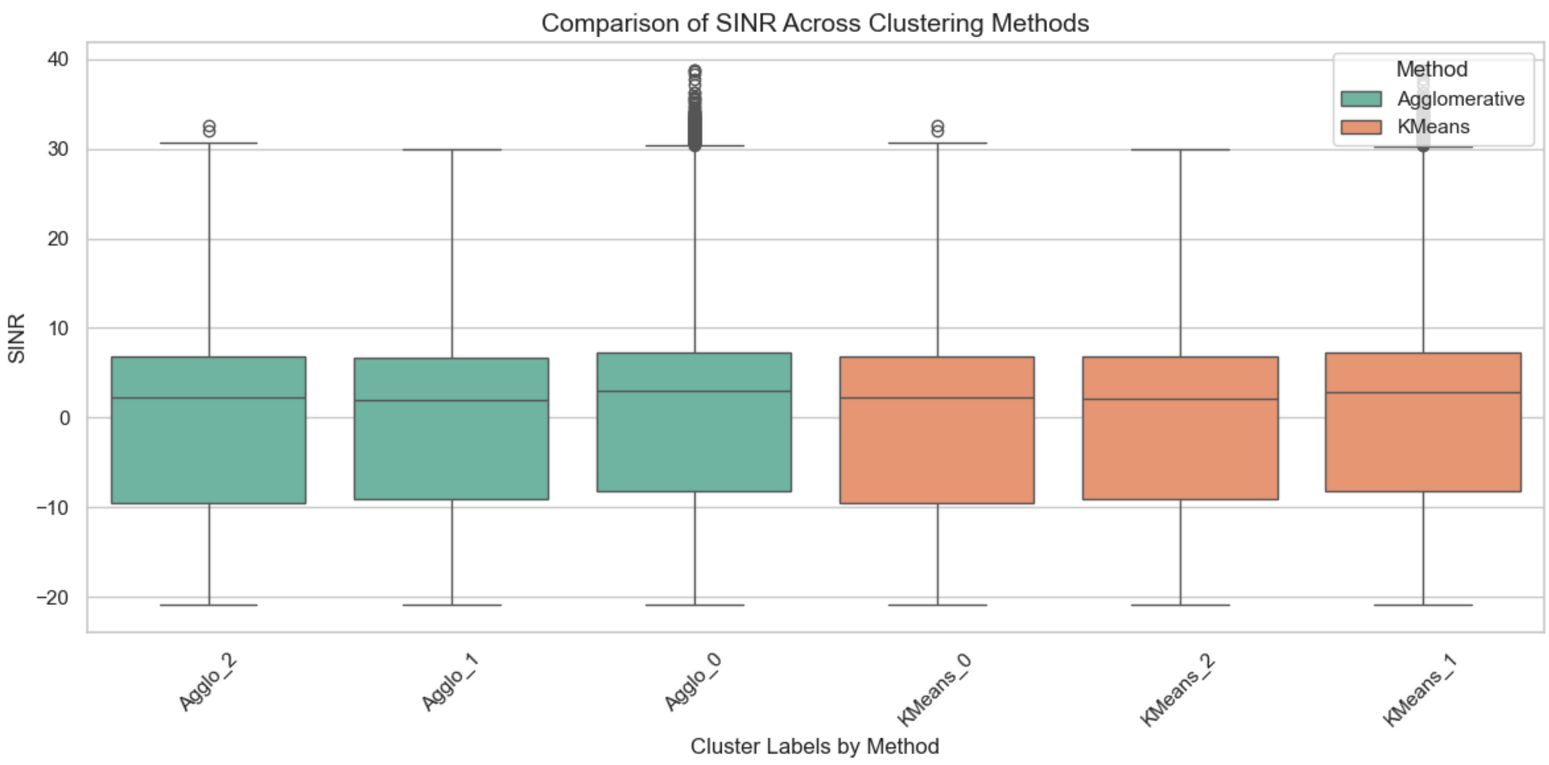
In [130…
```
# Define the features to compare across clustering methods
features = ['RSRP', 'RSRQ', 'Power', 'distance', 'SINR', 'Frequency', 'Speed']

# Convert cluster labels to string type for plotting
df['Agglo_Cluster'] = df['Agglo_Cluster'].astype(str)
df['KMeans_Cluster'] = df['KMeans_Cluster'].astype(str)

# Loop through each feature for plotting
for feature in features:
    # Prepare Agglomerative clustering data
    df_agglo = df[[feature, 'Agglo_Cluster']].copy()
    df_agglo['Cluster_Label'] = 'Agglo_' + df_agglo['Agglo_Cluster']
    df_agglo['Method'] = 'Agglomerative'

    # Prepare KMeans clustering data
    df_kmeans = df[[feature, 'KMeans_Cluster']].copy()
    df_kmeans['Cluster_Label'] = 'KMeans_' + df_kmeans['KMeans_Cluster']
    df_kmeans['Method'] = 'KMeans'

    # Rename feature column to unify
    df_agglo.rename(columns={feature: 'Value'}, inplace=True)
    df_kmeans.rename(columns={feature: 'Value'}, inplace=True)

    # Combine both datasets
    combined_df = pd.concat([df_agglo, df_kmeans], axis=0)

    # Plot using seaborn boxplot
    plt.figure(figsize=(12, 6))
    sns.boxplot(data=combined_df, x='Cluster_Label', y='Value', hue='Method', palette='Set2')

    # Title and labels
    plt.title(f'Comparison of {feature} Across Clustering Methods', fontsize=14)
    plt.xlabel('Cluster Labels by Method')
    plt.ylabel(feature)
    plt.xticks(rotation=45)
    plt.legend(title='Method', loc='upper right')
    plt.tight_layout()
    plt.show()
```

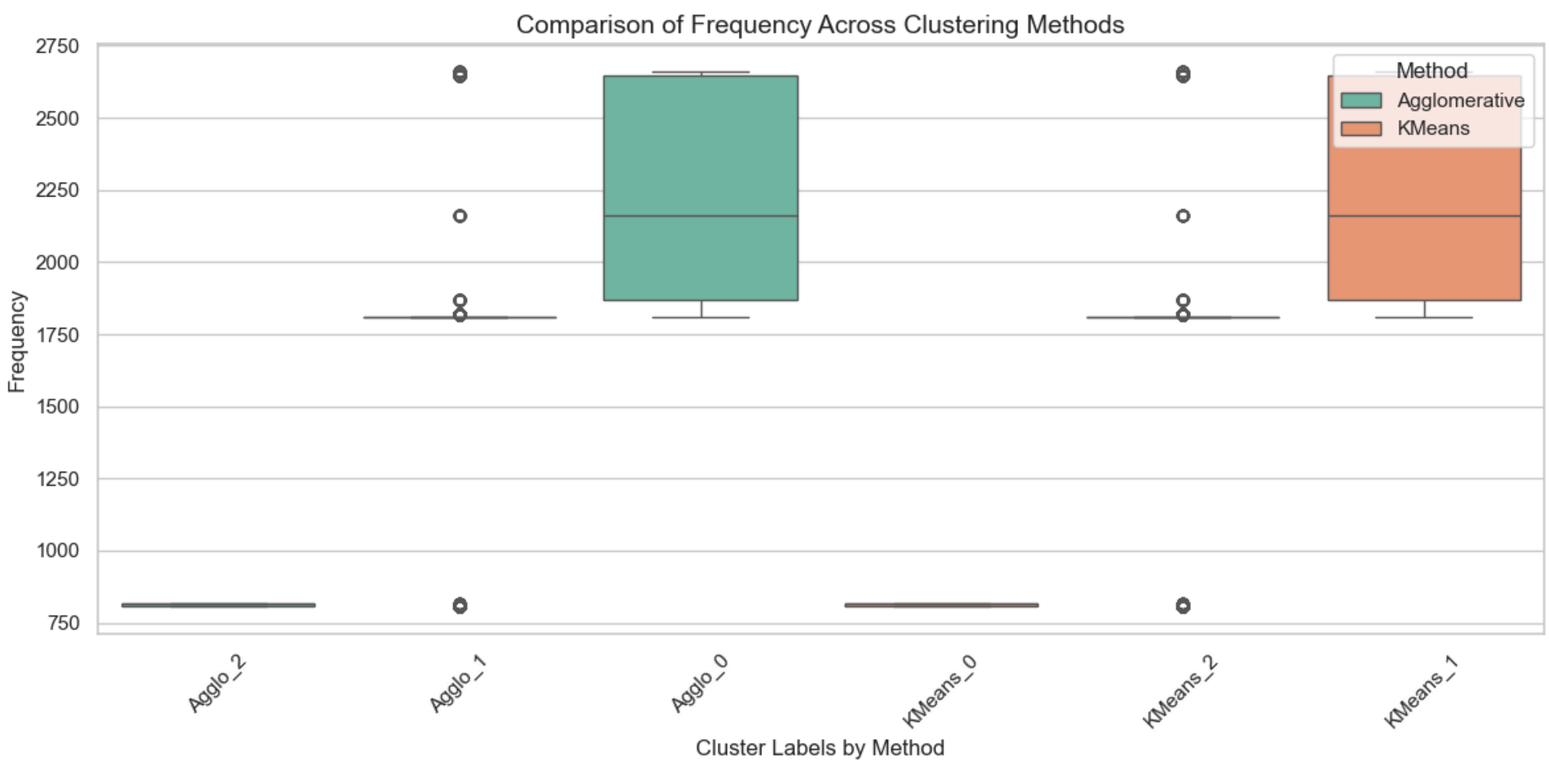

Comparison of RSRP Across Clustering Methods
RSRP
−60
−80
−100
−120
−140
Method
Agglomerative
KMeans
Agglo_2
Agglo_1
Agglo_0
KMeans_0
KMeans_2
KMeans_1
Cluster Labels by Method

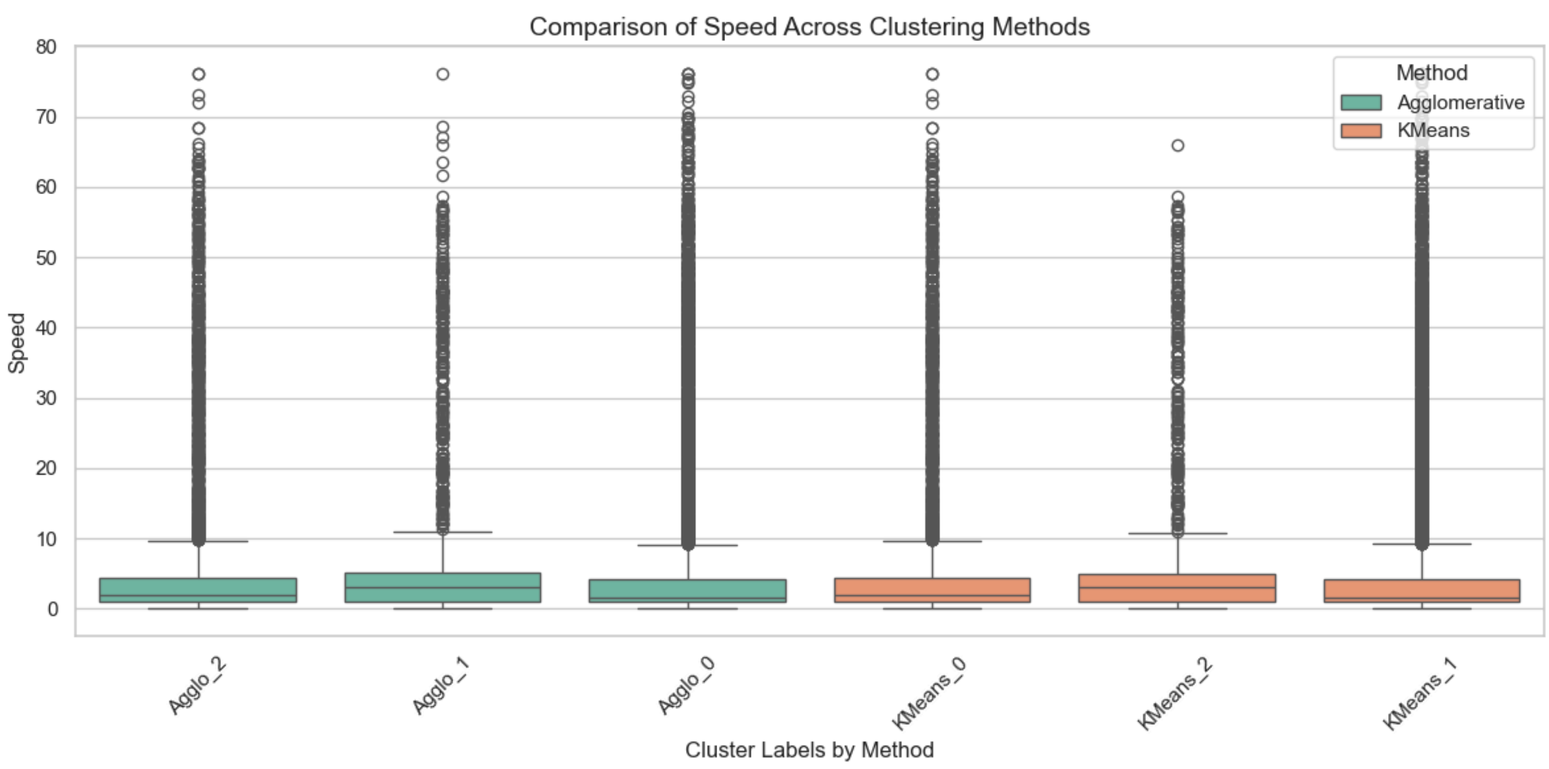

Comparison of RSRQ Across Clustering Methods
RSRQ
−10.0
−12.5
−15.0
−17.5
−20.0
−22.5
−25.0
−27.5
−30.0
Method
Agglomerative
KMeans
Agglo_2
Agglo_1
Agglo_0
KMeans_0
KMeans_2
KMeans_1
Cluster Labels by Method


Comparison of Power Across Clustering Methods
Power
−20
−40
−60
−80
−100
−120
Method
Agglomerative
KMeans
Agglo_2
Agglo_1
Agglo_0
KMeans_0
KMeans_2
KMeans_1
Cluster Labels by Method


Comparison of distance Across Clustering Methods
distance
8000
6000
4000
2000
0
Method
Agglomerative
KMeans
Agglo_2
Agglo_1
Agglo_0
KMeans_0
KMeans_2
KMeans_1
Cluster Labels by Method

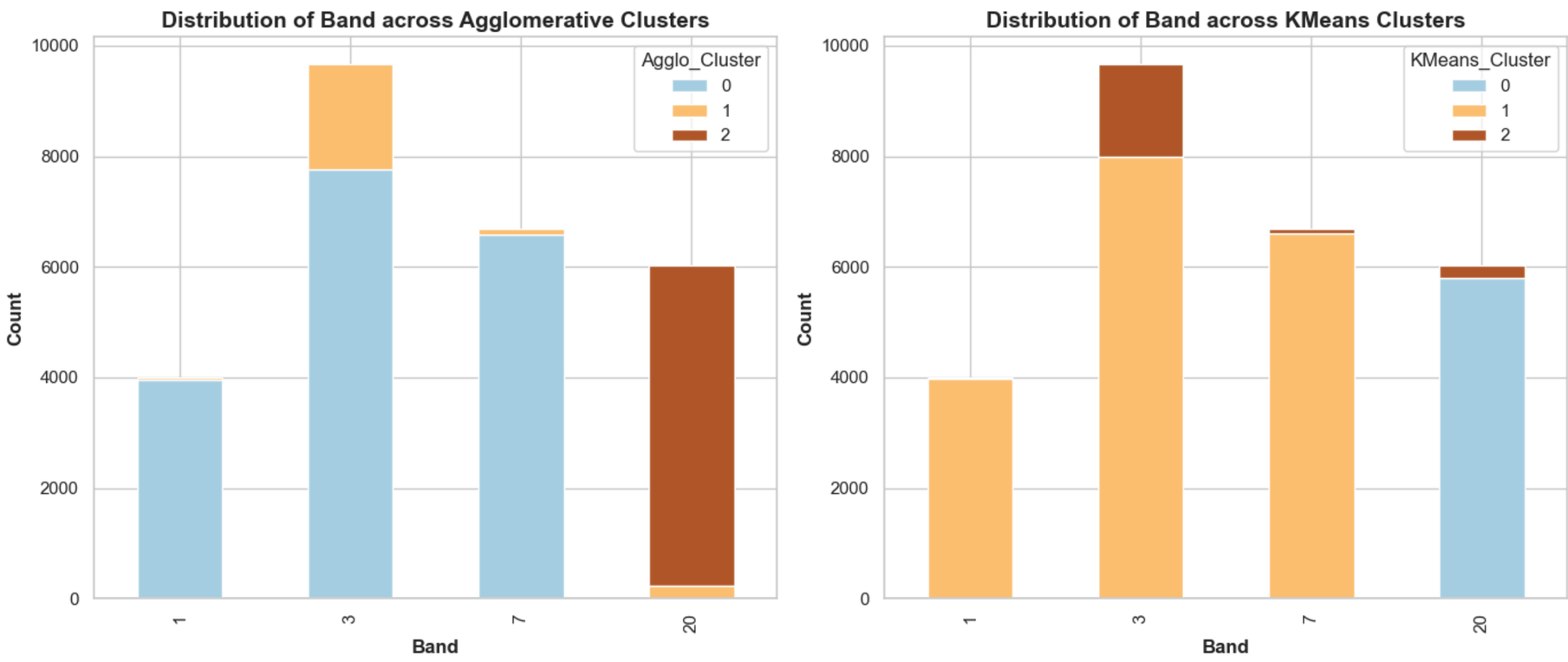


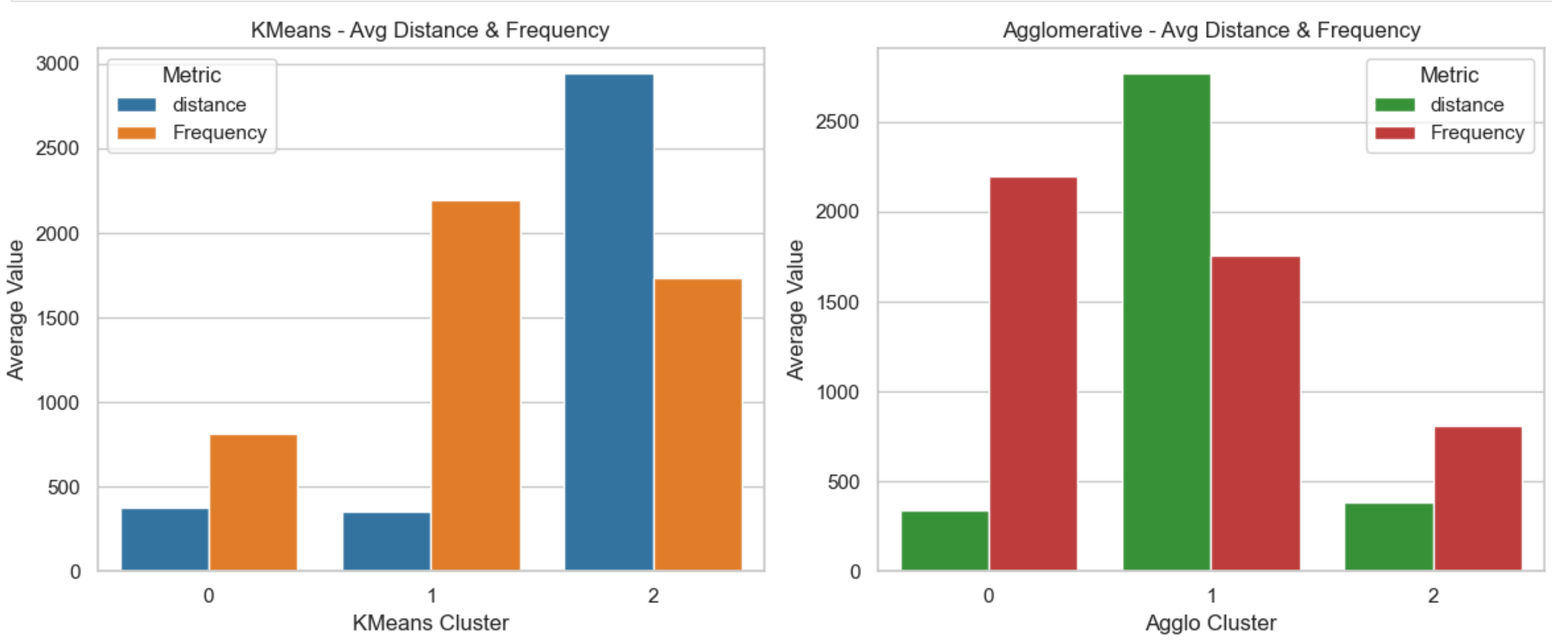

In [131…

```python
# Create cross-tab of Band frequency per cluster type
band_counts = pd.crosstab(df['Band'], df['Agglo_Cluster'])
band_counts_kmeans = pd.crosstab(df['Band'], df['KMeans_Cluster'])

# Create side-by-side bar charts
fig, axes = plt.subplots(1, 2, figsize=(14, 6))

# Plot Agglomerative clustering
band_counts.plot(kind='bar', stacked=True, colormap='Paired', ax=axes[0])
axes[0].set_title("Distribution of Band across Agglomerative Clusters", fontsize=14, fontweight="bold")
axes[0].set_xlabel("Band", fontsize=12, fontweight="bold")
axes[0].set_ylabel("Count", fontsize=12, fontweight="bold")
axes[0].legend(title="Agglo_Cluster")

# Plot KMeans clustering
band_counts_kmeans.plot(kind='bar', stacked=True, colormap='Paired', ax=axes[1])
axes[1].set_title("Distribution of Band across KMeans Clusters", fontsize=14, fontweight="bold")
axes[1].set_xlabel("Band", fontsize=12, fontweight="bold")
axes[1].set_ylabel("Count", fontsize=12, fontweight="bold")
axes[1].legend(title="KMeans_Cluster")

plt.tight_layout()  # Optimize spacing
plt.show()  # Display plots
```




The bar charts given above indicate how different frequency bands are distributed among the clusters identified by the Agglomerative and K-Means algorithms. The clustering distributions are different on a per-cluster basis. For example, Agglomerative clustering shows a stronger dominance of Band 20 in Cluster 2, while K-Means clustering assigns most of the Band 20 data to Cluster 0.

In [133…
```
# Grouping data by KMeans clusters and calculating the mean of distance and frequency
kmeans_grouped = df.groupby('KMeans_Cluster')[['distance', 'Frequency']].mean().reset_index()

# Reshaping the data for better visualization (melting columns into a long-format structure)
kmeans_grouped = pd.melt(kmeans_grouped, id_vars='KMeans_Cluster',
                         var_name='Metric', value_name='AvgValue')

# Similarly, grouping data by Agglomerative clusters and computing average distance and frequency
agglo_grouped = df.groupby('Agglo_Cluster')[['distance', 'Frequency']].mean().reset_index()

# Melting the dataframe to prepare it for visualization
agglo_grouped = pd.melt(agglo_grouped, id_vars='Agglo_Cluster',
                        var_name='Metric', value_name='AvgValue')

# Define color palettes for visual differentiation
kmeans_palette = ["#1f77b4", "#ff7f0e"]  # Blue and orange for KMeans cluster metrics
agglo_palette = ["#2ca02c", "#d62728"]  # Green and red for Agglomerative cluster metrics

# Creating a figure with two subplots to compare clustering results
fig, axes = plt.subplots(1, 2, figsize=(12, 5))  # Arrange plots side by side

# Plot for KMeans clustering results
sns.barplot(ax=axes[0], data=kmeans_grouped, x='KMeans_Cluster', y='AvgValue', hue='Metric', palette=kmeans_palette)
axes[0].set_title('KMeans - Avg Distance & Frequency')  # Setting title for clarity
axes[0].set_xlabel('KMeans Cluster')  # Labeling the x-axis
axes[0].set_ylabel('Average Value')  # Labeling the y-axis

# Plot for Agglomerative clustering results
sns.barplot(ax=axes[1], data=agglo_grouped, x='Agglo_Cluster', y='AvgValue', hue='Metric', palette=agglo_palette)
axes[1].set_title('Agglomerative - Avg Distance & Frequency')  # Providing an informative title
axes[1].set_xlabel('Agglo Cluster')  # Labeling the x-axis
axes[1].set_ylabel('Average Value')  # Consistent labeling with the KMeans plot

# Adjust layout for better spacing and readability
plt.tight_layout()

# Display the plots
plt.show()
```




The figure above illustrates differences in average distance and frequency for each cluster generated by K-Means and Agglomerative clustering. For example, Cluster 2 exhibits the highest average distance about 3000 meter in the K-Means model. This occurs in Cluster 1 of the Agglomerative model. These patterns highlight how each algorithm partitions the data differently in terms of distribution and density.

# 5. Classification (Task 3)

For the binary classification task, the feature MNC (Mobile Network Code) was selected as the target variable. This variable includes the network operator identifier and is quite suitable for binary classification due to its two distinct categories. Moreover, the class distribution is relatively balanced. "Op2" accounts for about 53.9% of the samples, while "Op1" represents 46.0%, which helps overcome the class imbalance issues during training. For the multi-class classification task, the scenario variable was selected as the target. This feature divides the measurement context into three categories: Outdoor Walking (OW), Indoor Stationary (IS), and Outdoor Driving (OD). These are important for modelling the changes in network performance in different real-world mobility scenarios. Moreover, the distribution of this variable is sufficiently diverse; OW is 43%, IS is 41% and OD is 16%, which makes it suitable for robust multi-class classification.

## 5.1. Binary Classification

### RandomForest Classifier

In [139…
```
df=df_cla.copy()  # using 100% of the dataset
del df_cla
```

In [140…
```
X = df[numeric_cols + categorical_cols].drop(columns=['MNC','CellIdentity','eNodeB.ID','EARFCN']) # dropping target columns and the columns which showed high correlation with target column
y = df["MNC"]
```

In [141…
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y) # train and test data split
```

In [142…
```
#  Train the model
rf_model = RandomForestClassifier(
    max_depth=2,
    random_state=42,
    n_jobs=-1
)
rf_model.fit(X_train, y_train)
```

Out[142…
```
RandomForestClassifier(max_depth=2, n_jobs=-1, random_state=42)
```

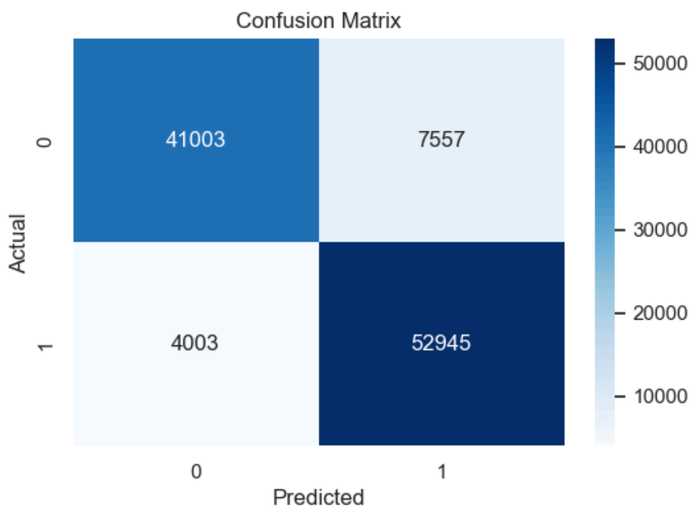
In [143…
```
# Make predictions
y_pred_rf = rf_model.predict(X_test)
```

In [144…
```
# Accuracy and F1 score
acc = accuracy_score(y_test, y_pred_rf)
f1 = f1_score(y_test, y_pred_rf, average='binary')
print(f"Accuracy: {acc:.4f}")
print(f"F1 Score: {f1:.4f}")
```

```
Accuracy: 0.8904
F1 Score: 0.9016
```

In this step the max_depth parameter was limited to reduce overfitting risk and the remaining hyperparameters were kept at default values. This approach provided a balance between model complexity and generalizability. After training the model, the results were visualized. As shown i nfigurebelow1, the confusion matrix highlights the strong performance of the model with 0.89 accuracy and 0.90 F1 score. These metrics indicate that the model is well balanced not only in accuracy metric but also in terms of precision and recall. The relatively low number of false positives and false negatives further supports its reliability in correctly classifying both classe

In [146…
```
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(y_test), yticklabels=np.unique(y_test))
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```




In [147…
```
# Classification Report
print("Classification Report:\n")
print(classification_report(y_test, y_pred_rf))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.91      0.84      0.88     48560
           1       0.88      0.93      0.90     56948

    accuracy                           0.89    105508
   macro avg       0.89      0.89      0.89    105508
weighted avg       0.89      0.89      0.89    105508
```

In [148…
```
# Feature Importance
importances = rf_model.feature_importances_
indices = np.argsort(importances)[::-1]
features = X_train.columns

# Plot
plt.figure(figsize=(10, 6))
sns.barplot(x=importances[indices][:15], y=features[indices][:15], palette='viridis')
plt.title("Top 15 Feature Importances - Random Forest")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.tight_layout()
plt.show()
```

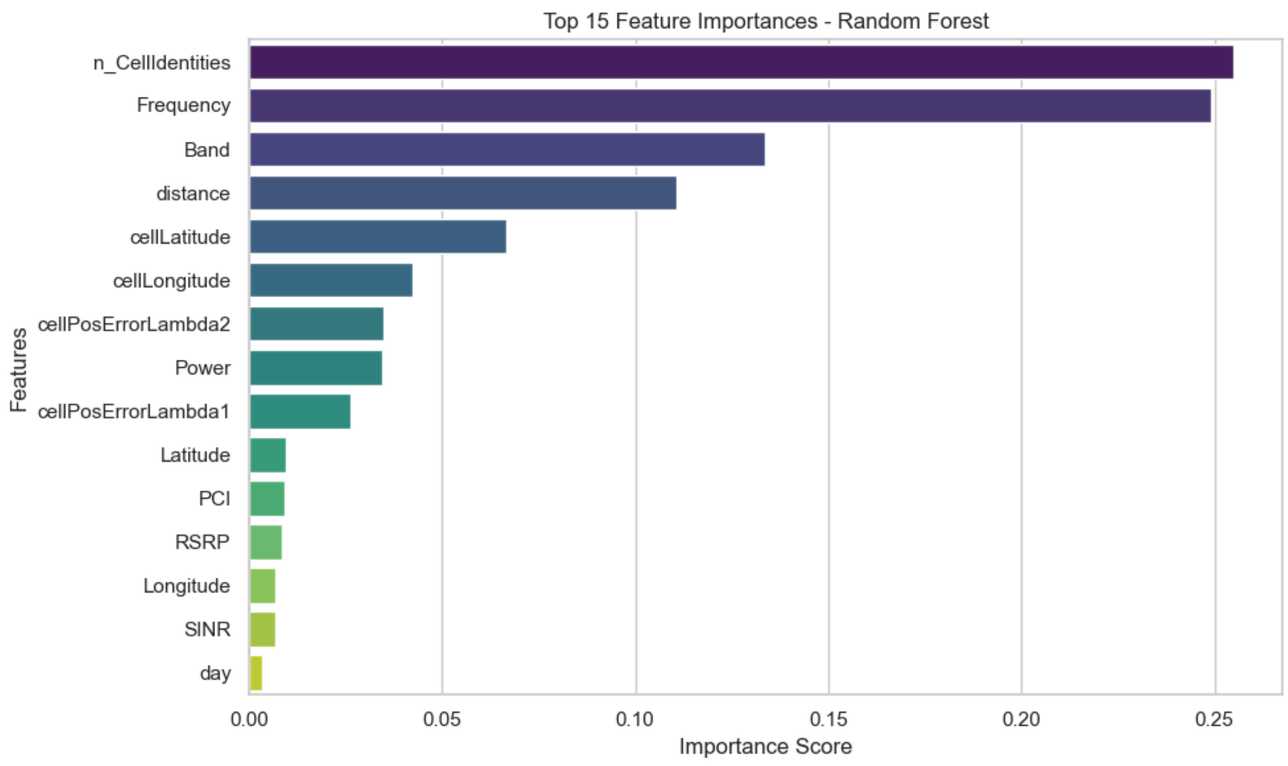
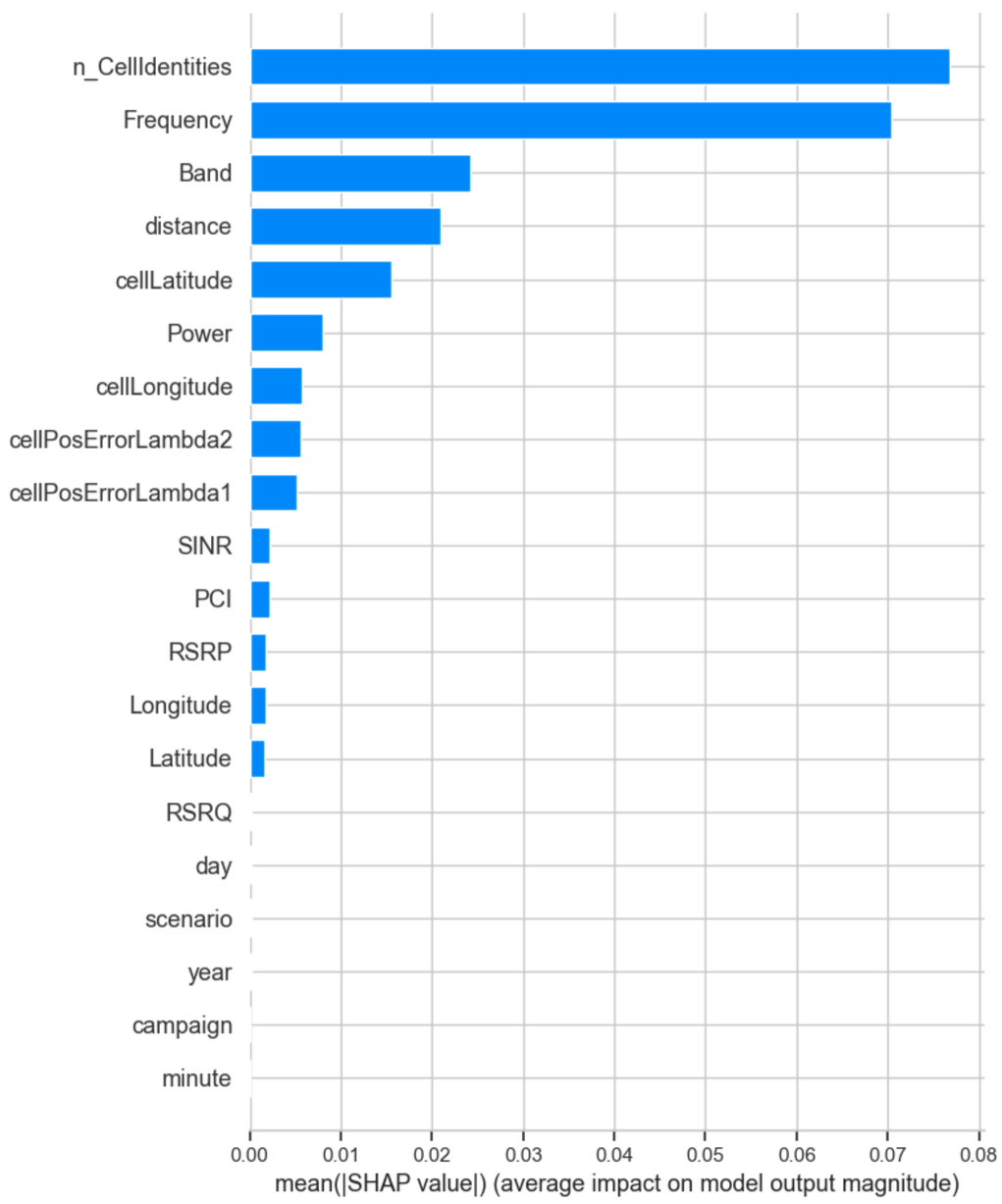


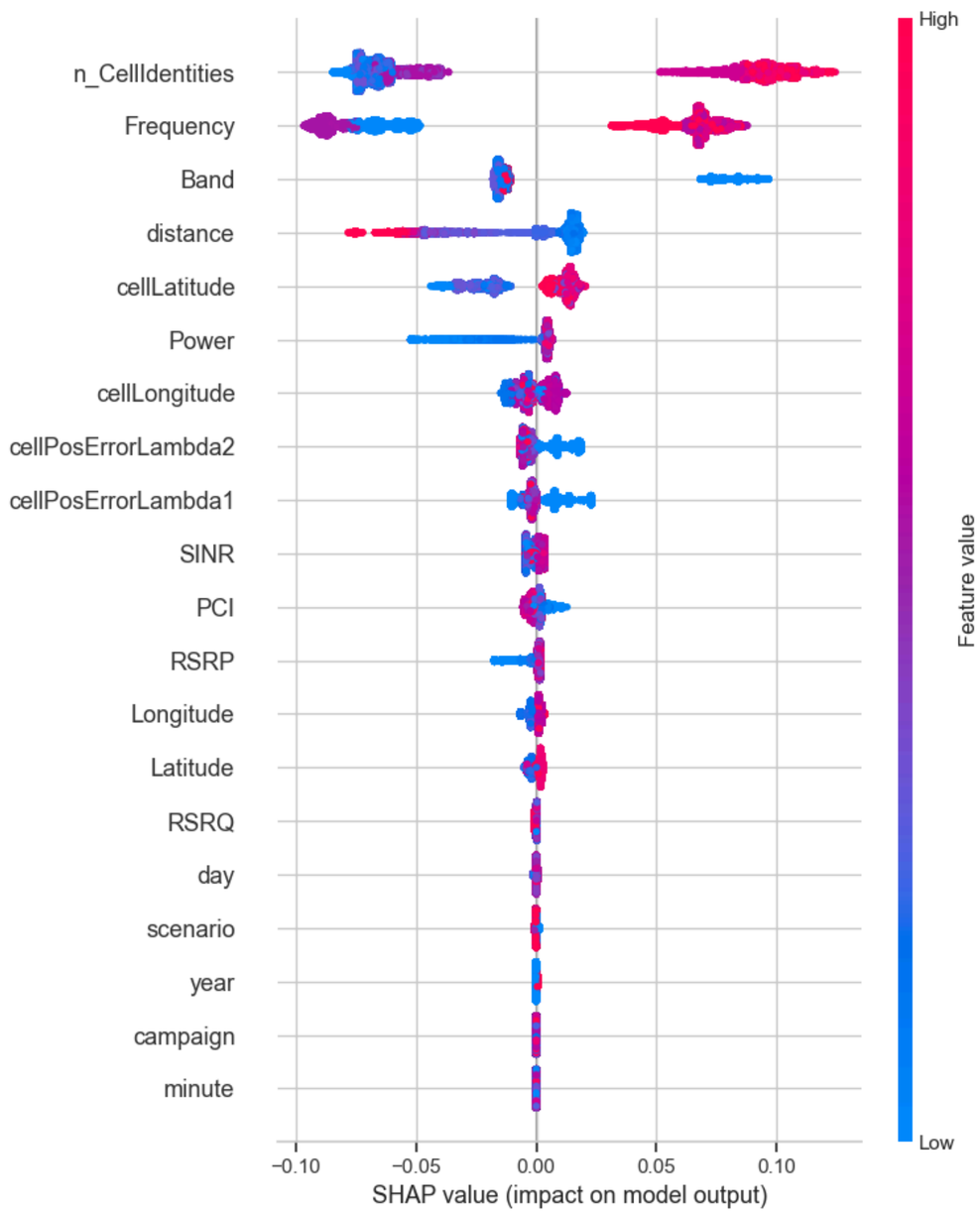

Figure given above illustrates the top 15 feature importances derived from the Random Forest classification model used in the binary classification task. The most significant feature is n_CellIdentities, followed closely by Frequency and Band. This indicates their critical role in model decision-making. Features such as distance, cellLatitude, and cellLongitude also contribute significantly to the classification outcome. In contrast, variables like day, SINR, and Longitude appear to have minimal impact. These ranking highlights which input variables are most informative for model.

In this study, SHAP (SHapley Additive exPlanations) analysis was employed as an additional method for interpreting the Random Forest binary classification model. SHAP assigns each feature an importance value for a particular prediction, offering both global and local interpretability. By quantifying the contribution of each feature to the model's output, SHAP provides a nuanced understanding of feature impacts beyond traditional importance metrics (Lundberg and Lee, 2017).

In [151…
```
# SHAP Analysis - Explain model predictions using SHAP values
explainer = shap.TreeExplainer(rf_model)
shap_values = explainer.shap_values(X_test)

# Check the shape of SHAP values
print("SHAP Values Shape:", np.array(shap_values).shape)

if isinstance(shap_values, list):  # If SHAP values are returned as a list
    shap_values_selected = shap_values[1]  # Take SHAP values for class "1"
else:
    shap_values_selected = shap_values[:, :, 1]  # Extract SHAP values for class 1 from a multi-dimensional array

# Verify the corrected shape
print("Corrected SHAP Shape:", shap_values_selected.shape)

# If the shape does not match the expected format, reshape the values
if shap_values_selected.shape[1] != X_test.shape[1]:
    shap_values_selected = shap_values_selected.reshape(X_test.shape)

# Generate summary plot (Bar format) - Shows feature importance
shap.summary_plot(shap_values_selected, X_test, plot_type="bar")

# Generate full summary plot - Shows feature impact on predictions
shap.summary_plot(shap_values_selected, X_test)
```

```
SHAP Values Shape: (105508, 26, 2)
Corrected SHAP Shape: (105508, 26)
```




The figure given above presents the SHAP value summary plot for the Random Forest binary classification model, providing insight into each feature's impact on model predictions. The plot highlights that n_CellIdentities, Frequency, and Band are the most influential features, with higher SHAP values indicating a stronger effect on the prediction output. The colour gradient represents the feature value, where red denotes high values and blue denotes low values. Notably, high values of Frequency tend to push the prediction towards one class, while low values of distance and cellLatitude are associated with a shift toward the other class.

## Logistic Regression Classfication

In [154…
```
# Initialize and train the Logistic Regression model
# - Set random_state for reproducibility
# - Increase max_iter to ensure convergence
log_model = LogisticRegression(random_state=42, max_iter=1000)
log_model.fit(X_train, y_train)
```

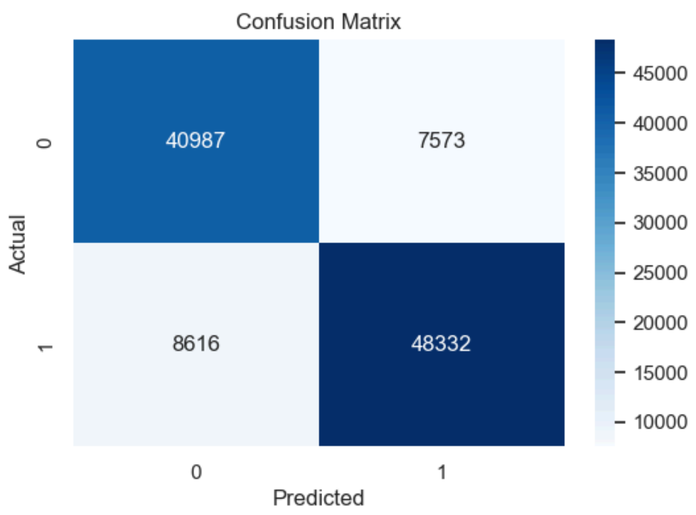
Out[154…
```
LogisticRegression(max_iter=1000, random_state=42)
```

In [155…
```
# Make predictions on the test set
y_pred_lr = log_model.predict(X_test)
```

In [156…
```
# Evaluate model performance
print("Accuracy:", accuracy_score(y_test, y_pred_lr))  # Prints overall accuracy
print("Classification Report:\n", classification_report(y_test, y_pred_lr))  # Precision, recall, F1-score per class
```

```
Accuracy: 0.8465613981878152
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.84      0.84     48560
           1       0.86      0.85      0.86     56948

    accuracy                           0.85    105508
   macro avg       0.85      0.85      0.85    105508
weighted avg       0.85      0.85      0.85    105508
```

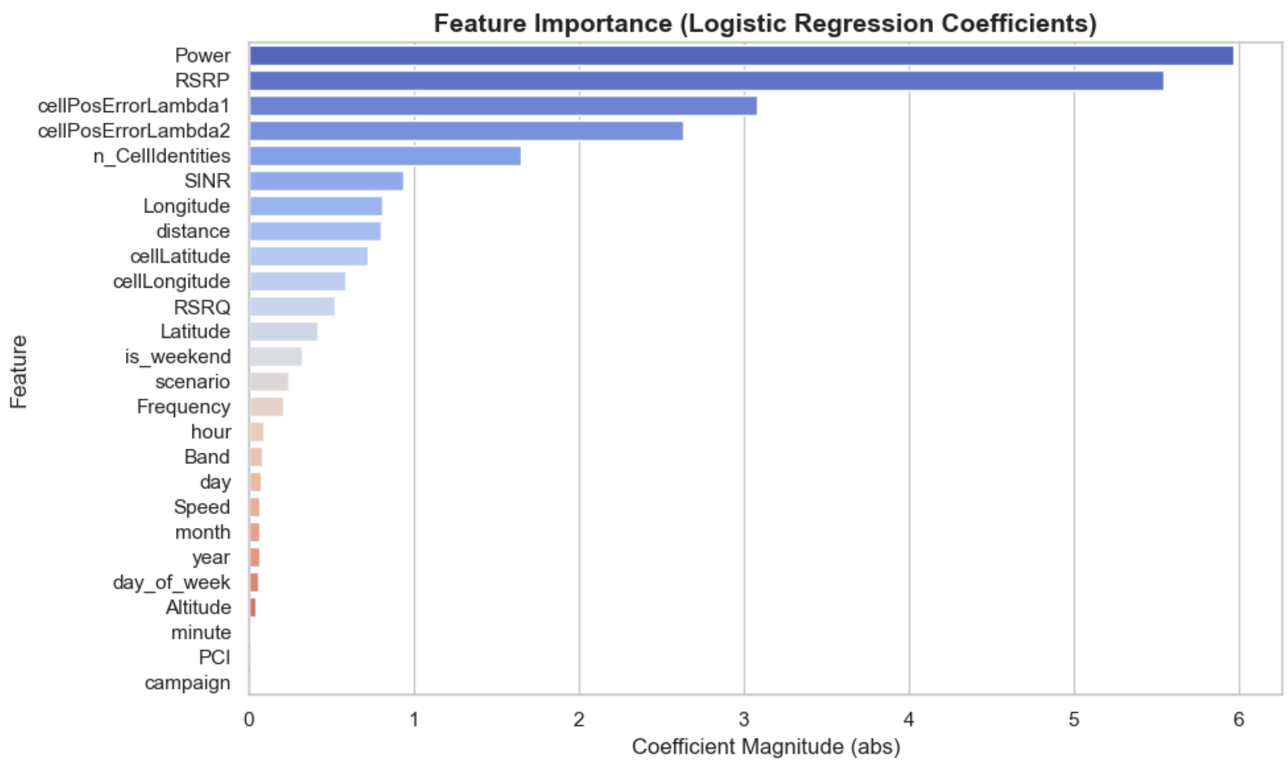
In [157…
```
# Confusion Matrix visualization to analyze misclassifications
cm = confusion_matrix(y_test, y_pred_lr)  # Generate confusion matrix
plt.figure(figsize=(6, 4))  # Set figure size
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')  # Create heatmap
plt.xlabel("Predicted")  # Label x-axis
plt.ylabel("Actual")  # Label y-axis
plt.title("Confusion Matrix")  # Set plot title
plt.show()
```




The confusion matrix shows that the model correctly predicted 40,987 class 0 instances and 48,332 class 1 instances. Meanwhile, 7,573 false positives and 8,616 false negatives were recorded. These results indicate a well-performing classifier with a good balance between precision and recall. Moreover, Logistic Regression was a successful model with an accuracy result of 0.85.

In [159…

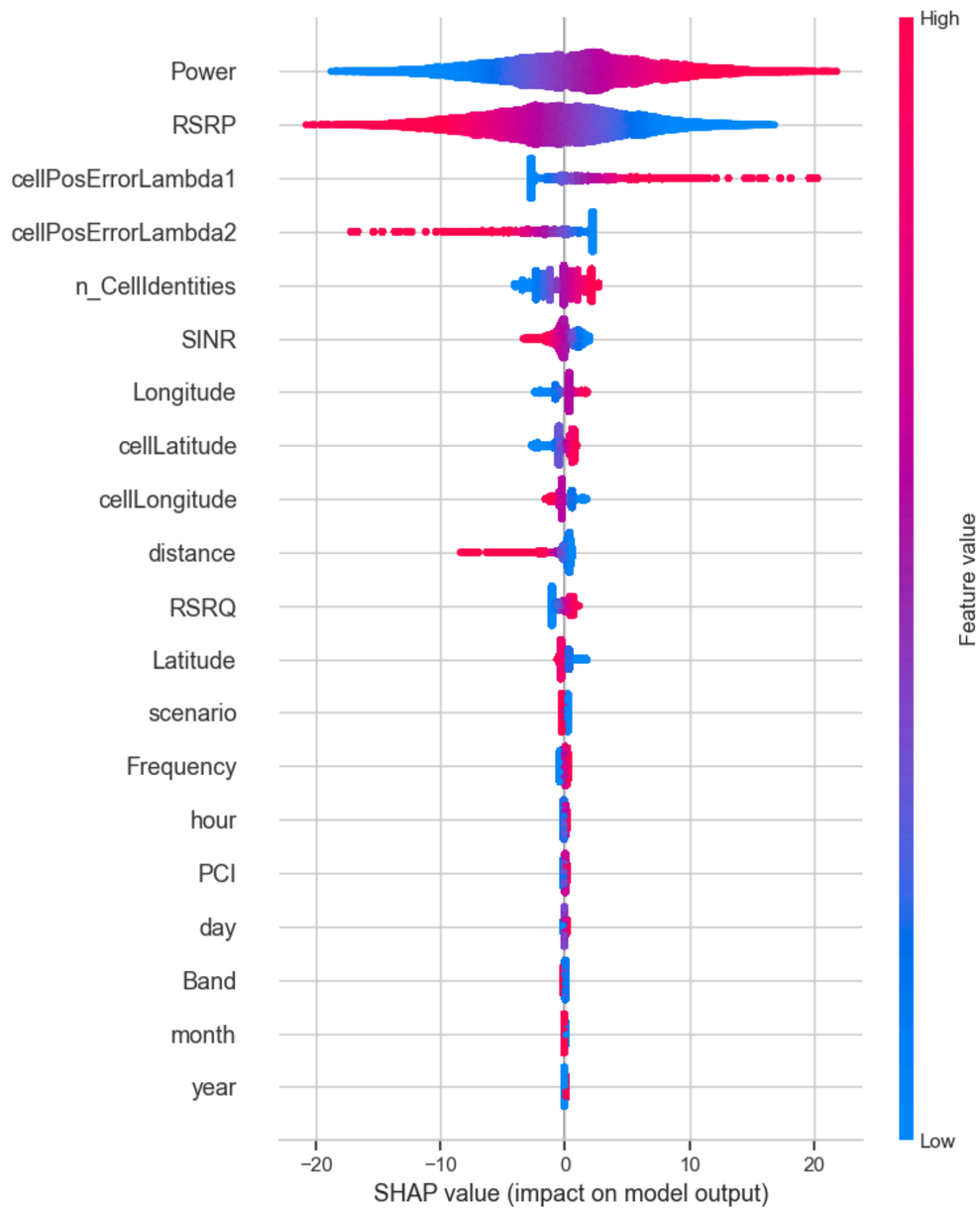
```
# Feature Importance (Coefficient-Based)
# - Logistic Regression coefficients represent the importance of features
# - Higher absolute values indicate stronger influence on predictions
coefficients = log_model.coef_[0]  # Extract coefficients (for binary classification)
feature_names = X_train.columns  # Get feature names

# Create a DataFrame to store feature importance
coef_df = pd.DataFrame({
    'Feature': feature_names,  # Feature names
    'Coefficient': coefficients,  # Raw coefficients
    'Importance': np.abs(coefficients)  # Absolute magnitude for importance ranking
}).sort_values(by='Importance', ascending=False)  # Sort by importance

# Visualizing feature importance using a bar plot
plt.figure(figsize=(10, 6))  # Set figure size
sns.barplot(x='Importance', y='Feature', data=coef_df, palette='coolwarm')
plt.title("Feature Importance (Logistic Regression Coefficients)", fontsize=14, fontweight='bold')
plt.xlabel("Coefficient Magnitude (abs)", fontsize=12)
plt.ylabel("Feature", fontsize=12)
plt.tight_layout()
plt.show()
```




The plot given above presents the feature importance values based on the absolute magnitude of the coefficients obtained from the Logistic Regression model applied to the binary classification task. Among all the features, Power and RSRP showed the highest importance. This indicated that signal strength features are the main determinants in the classification decision process. They are followed by cellPosErrorLambda1, cellPosErrorLambda2 and n_CellIdentities, which show the cell identity and error amounts, which are clearly effective factors in predicting the target class. Moderately important features include SINR, Longitude and Distance. This showed that signal quality and location information are still important for algorithm.

In [161…

```
# SHAP explainer
explainer = shap.LinearExplainer(log_model, X_train, feature_perturbation="interventional")

# calculate SHAP values
shap_values = explainer.shap_values(X_test)

# summary plot: effect of the features
shap.summary_plot(shap_values, X_test, feature_names=X_test.columns)
```

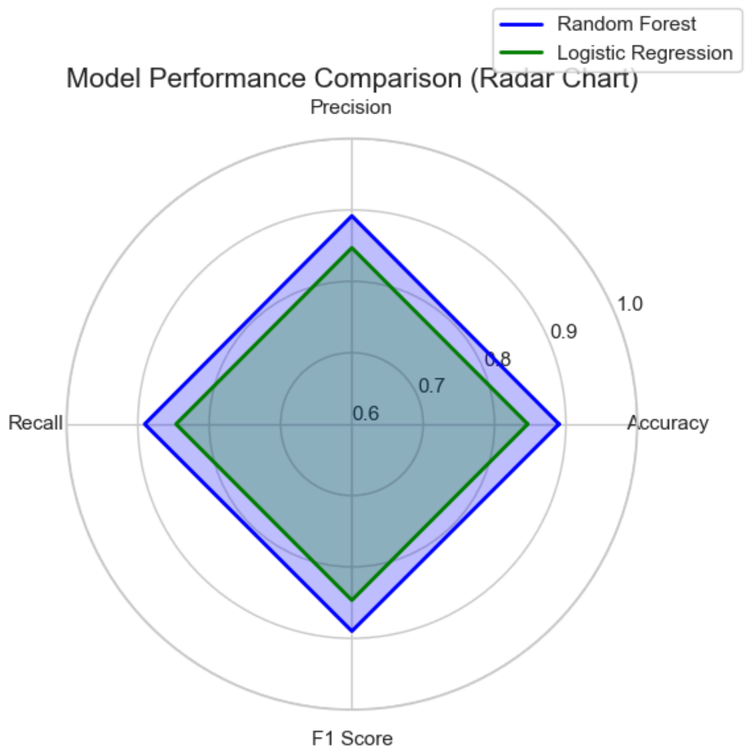



The plot given above indicates the SHAP value summary plot for the Logistic Regression model used in the binary classification task. This visualization provides both the magnitude and direction of the contribution of each feature to the model's predictions. To begin with, Power and RSRP are the most influential features and consistently affect the model output positively or negatively depending on their values. For instance, high Power values generally lead to a positive SHAP value indicating an increased probability of a particular class, while low values contribute negatively. Similarly, cellPosErrorLambda1, cellPosErrorLambda2, and n_CellIdentities also show a significant effect. This suggests that cell location error margins are important variables.

In [163…

```
# Evaluate metrics
rf_scores = [
```

```
    accuracy_score(y_test, y_pred_rf),
    precision_score(y_test, y_pred_rf, average='weighted'),
    recall_score(y_test, y_pred_rf, average='weighted'),
    f1_score(y_test, y_pred_rf, average='weighted')
]

lr_scores = [
    accuracy_score(y_test, y_pred_lr),
    precision_score(y_test, y_pred_lr, average='weighted'),
    recall_score(y_test, y_pred_lr, average='weighted'),
    f1_score(y_test, y_pred_lr, average='weighted')
]

# Labels and angles
labels = ['Accuracy', 'Precision', 'Recall', 'F1 Score']
num_vars = len(labels)

# Close the plot by repeating the first value
angles = np.linspace(0, 2 * np.pi, num_vars, endpoint=False).tolist()
angles += angles[:1]  # close the radar chart

rf_scores += [rf_scores[0]]
lr_scores += [lr_scores[0]]

# Create the radar chart
fig, ax = plt.subplots(figsize=(8, 6), subplot_kw=dict(polar=True))

# Plot each model
ax.plot(angles, rf_scores, color='blue', linewidth=2, label='Random Forest')
ax.fill(angles, rf_scores, color='blue', alpha=0.25)

ax.plot(angles, lr_scores, color='green', linewidth=2, label='Logistic Regression')
ax.fill(angles, lr_scores, color='green', alpha=0.25)

# Formatting
ax.set_title("Model Performance Comparison (Radar Chart)", fontsize=15)
ax.set_xticks(angles[:-1])
ax.set_xticklabels(labels)
ax.set_yticks([0.6, 0.7, 0.8, 0.9, 1.0])
ax.set_ylim(0.6, 1.0)
ax.legend(loc='lower right', bbox_to_anchor=(1.2, 1.1))

plt.tight_layout()
plt.show()
```




The radar chart presents a comparative visual of the models applied for binary classification. In the binary classification task, both Random Forest and Logistic Regression models showed strong performance, albeit with different strengths. Random Forest model achieved an accuracy of 0.89. In contrast, Logistic Regression achieved an accuracy of 0.85, offering better interpretability thanks to the coefficient-based feature importance. Feature analysis revealed that signal-related variables such as RSRP and Power were consistently significant in both models. However, Random Forest made more use of categorical features such as n_CellIdentities and Band. Overall, Random Forest was more accurate. Also, Logistic Regression provided clearer insights into feature effects.

## 5.2. Multi-Class Classification

In [166…
```
X = df[categorical_cols + numeric_cols].drop(columns=["scenario","campaign"]) # dropping target columns and the columns which showed high correlation with target column
y = df[categorical_cols + numeric_cols]["scenario"]
```

In [167…
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y,  shuffle=True) # train and test data splitting
```

In [168…
```
#  Train the model
rf_model = RandomForestClassifier(
    max_depth=5,
    random_state=42,
    n_jobs=-1                #
)
rf_model.fit(X_train, y_train)
```

Out[168…

RandomForestClassifier

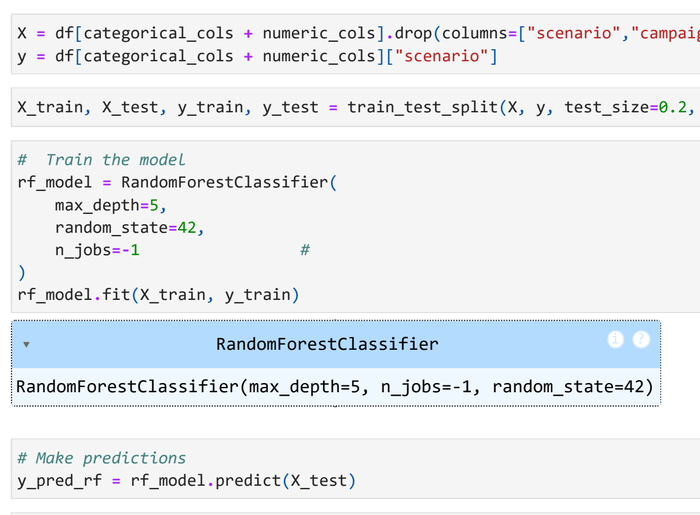
```
RandomForestClassifier(max_depth=5, n_jobs=-1, random_state=42)
```

In [169…
```
# Make predictions
y_pred_rf = rf_model.predict(X_test)
```

In [170…
```
# Accuracy and F1 score
acc = accuracy_score(y_test, y_pred_rf)
f1 = f1_score(y_test, y_pred_rf, average='macro')  # Using 'macro'  for multi-class
print(f"Accuracy: {acc:.4f}")
print(f"F1 Score: {f1:.4f}")
```

```
Accuracy: 0.9067
F1 Score: 0.9109
```

In [171…
```
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(6, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=np.unique(y_test), yticklabels=np.unique(y_test))
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```




The confusion matrix reveals that the model correctly predicted 39,268 class 0 instances, 14,491 class 1 instances, and 41,905 class 2 instances. However, the model misclassified 4,058 class 0 instances, 1,485 class 1 instances, and 3,467 class 2 instances. Besides, 829 class 1 instances were incorrectly classified as class 0, while 4 class 0 and 1 class 2 instance were predicted as class 1. These results show that the Random Forest model exhibits a strong ability to generalize across multiple classes with minimal misclassification. The classifier achieved an overall F1 Score of 0.91, further validating its robustness and reliability for multi-class prediction tasks.

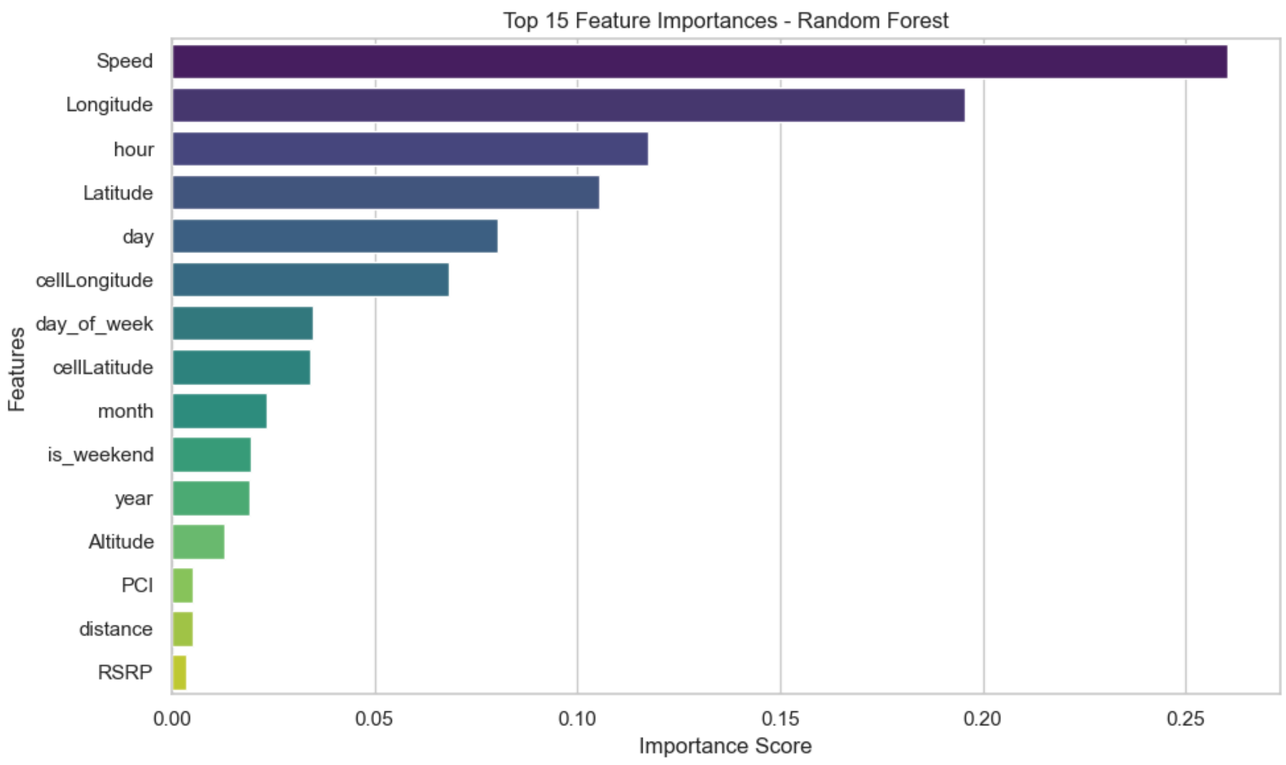
In [173…
```
# Classification Report
print("Classification Report:\n")
print(classification_report(y_test, y_pred_rf))
```

Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.90 | 0.91 | 0.90 | 43330 |
| 1 | 1.00 | 0.86 | 0.93 | 16805 |
| 2 | 0.88 | 0.92 | 0.90 | 45373 |
| accuracy | | | 0.91 | 105508 |
| macro avg | 0.93 | 0.90 | 0.91 | 105508 |
| weighted avg | 0.91 | 0.91 | 0.91 | 105508 |

In [174…

```
# Feature Importance
importances = rf_model.feature_importances_
indices = np.argsort(importances)[::-1]
features = X_train.columns

# Plot
plt.figure(figsize=(10, 6))
sns.barplot(x=importances[indices][:15], y=features[indices][:15], palette='viridis')
plt.title("Top 15 Feature Importances - Random Forest")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.tight_layout()
plt.show()
```

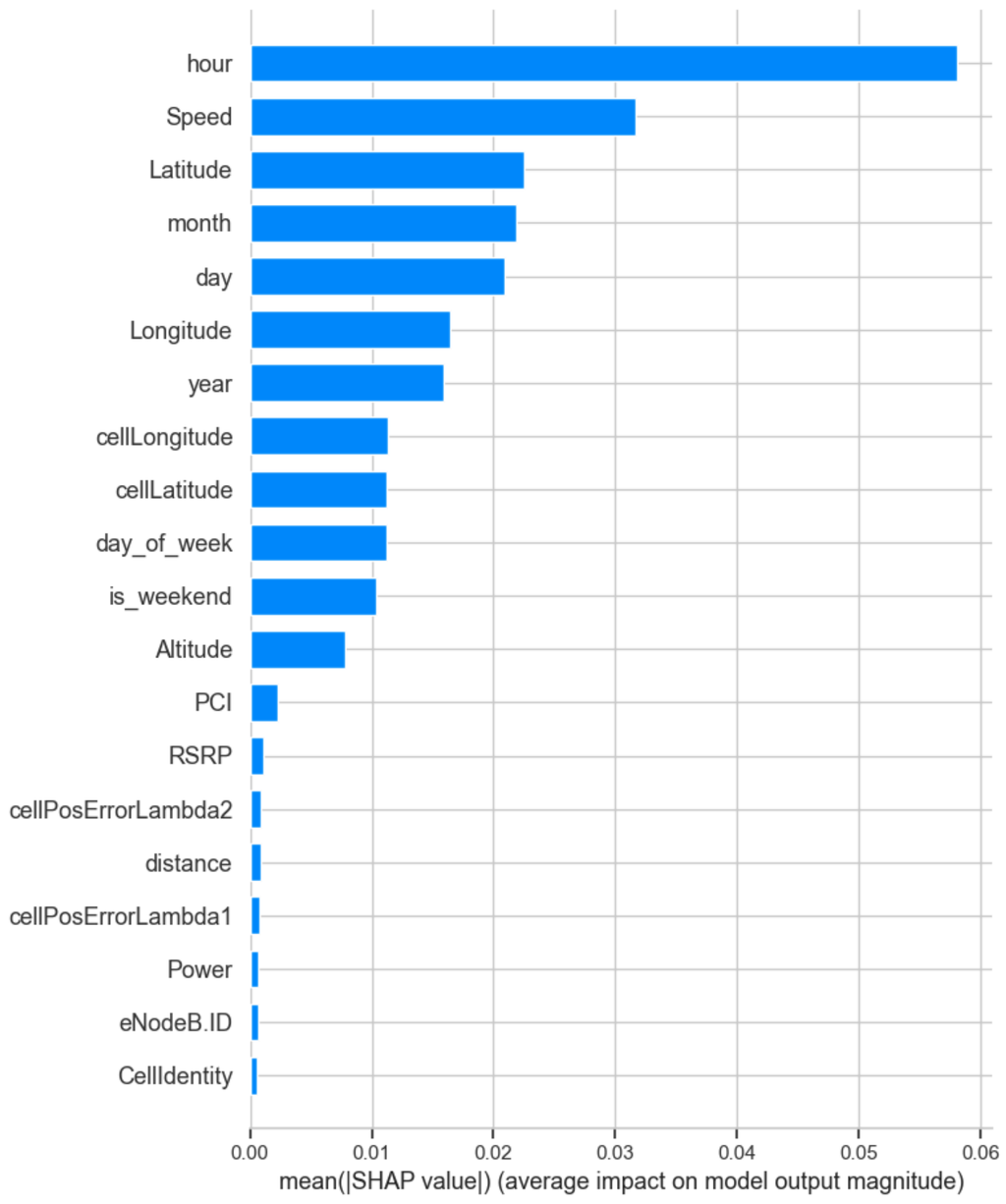


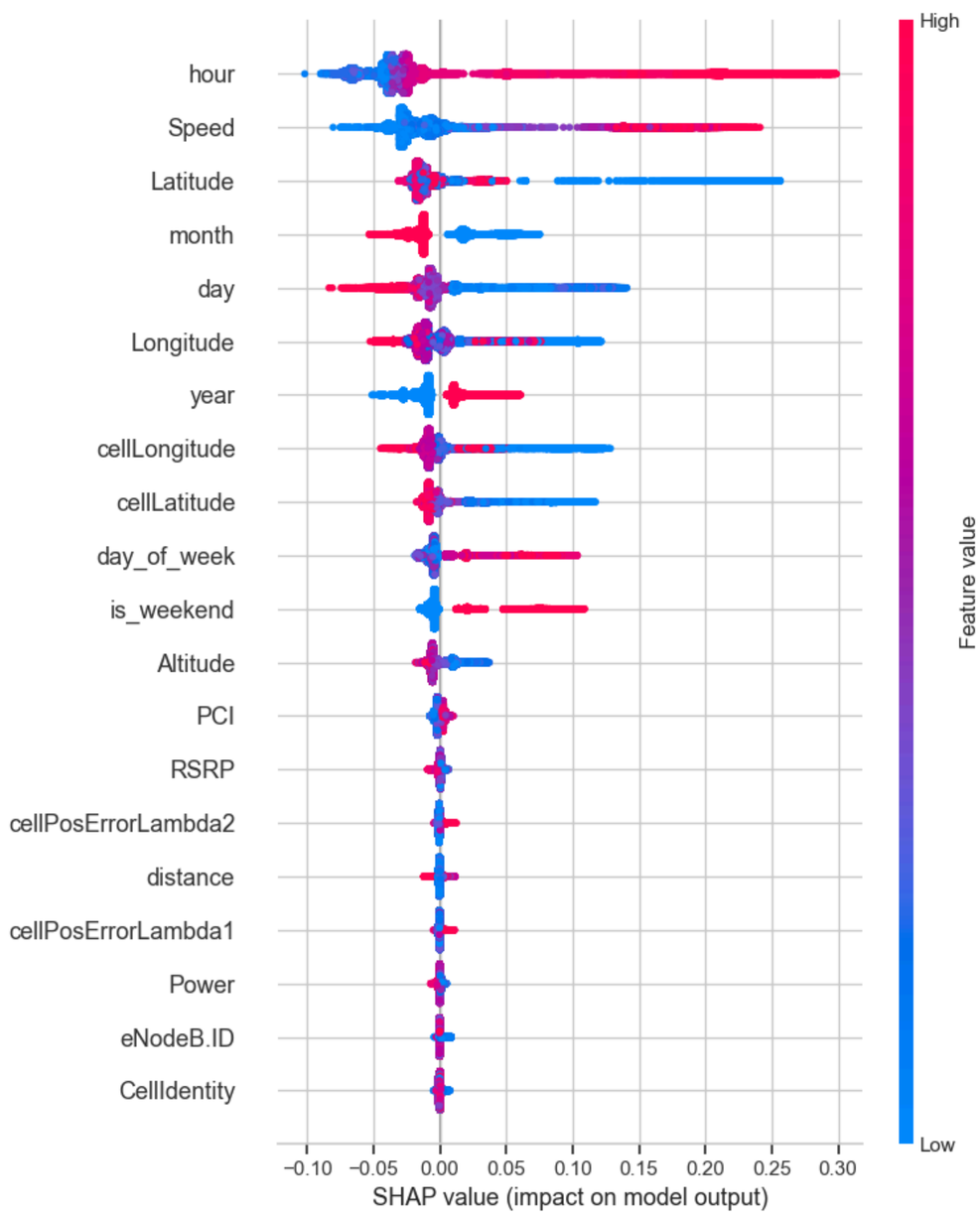

The figure given above indicates the top 15 features used by the Random Forest model. Accordingly, it shows that Speed is the most effective factor in predicting the scenario variable, followed by Longitude, Time and Latitude. These top features indicate that user movement patterns and location play a significant role in determining whether a scenario is classified as indoor, outdoor or other types. Temporal features such as day and time, together with contextual indicators such as cellLongitude and is_weekend, contribute significantly to the model's decision-making process. This insight highlights how both mobility and spatiotemporal factors are strongly related to the network usage context. It also highlights how the classifier effectively distinguishes between different user environments.

In [176…

```
# SHAP Analysis - Explain model predictions using SHAP values
explainer = shap.TreeExplainer(rf_model)
shap_values = explainer.shap_values(X_test)

# Check the shape of SHAP values
print("SHAP Values Shape:", np.array(shap_values).shape)

if isinstance(shap_values, list):  # If SHAP values are returned as a list
    shap_values_selected = shap_values[1]  # Take SHAP values for class "1"
else:
    shap_values_selected = shap_values[:, :, 1]  # Extract SHAP values for class 1 from a multi-dimensional array

# Verify the corrected shape
print("Corrected SHAP Shape:", shap_values_selected.shape)

# If the shape does not match the expected format, reshape the values
if shap_values_selected.shape[1] != X_test.shape[1]:
    shap_values_selected = shap_values_selected.reshape(X_test.shape)

# Generate summary plot (Bar format) - Shows feature importance
shap.summary_plot(shap_values_selected, X_test, plot_type="bar")

# Generate full summary plot - Shows feature impact on predictions
shap.summary_plot(shap_values_selected, X_test)
```

```
SHAP Values Shape: (105508, 28, 3)
Corrected SHAP Shape: (105508, 28)
```






The SHAP value plot provides a comprehensive interpretation of how individual features contribute to the classification of the Scenario variable. Features such as hour, speed, and latitude exhibit the highest SHAP values, indicating that they have a strong influence on the model's output. Higher speed values are associated with increased probability of outdoor scenarios, while lower values correspond to more static environments such as indoor scenario. Similarly, hour and day reflect the temporal dynamics that affect scenario classification, with certain time intervals showing distinct patterns of behaviour.

### Logistic Regression Classification (Multinomial)

In [179…
```python
# Initialize and train the Logistic Regression model
# Set random_state for reproducibility
log_model = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=1000, random_state=42)
log_model.fit(X_train, y_train)
```

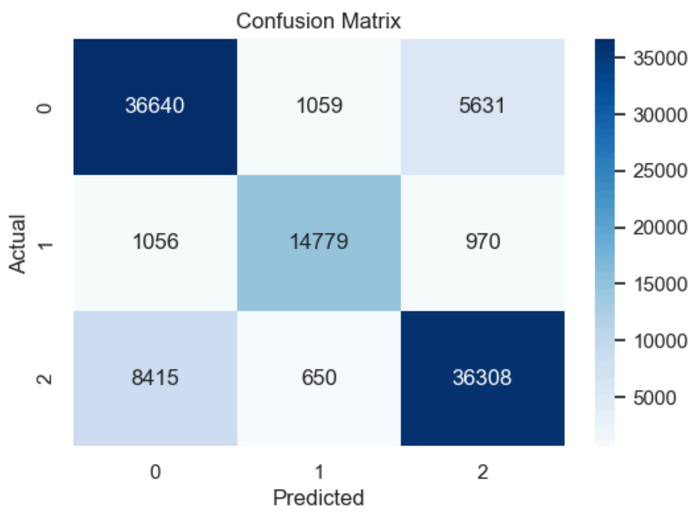
Out[179…
```
LogisticRegression(max_iter=1000, multi_class='multinomial', random_state=42)
```

In [180…
```python
# Make predictions on the test set
y_pred_lr = log_model.predict(X_test)
```

In [181…
```python
# Accuracy and F1 score
acc = accuracy_score(y_test, y_pred_lr)
f1 = f1_score(y_test, y_pred_lr, average='macro')  # Using 'macro' for multi-class
print(f"Accuracy: {acc:.4f}")
print(f"F1 Score: {f1:.4f}")

print("Classification Report:\n", classification_report(y_test, y_pred_lr))  # Precision, recall, F1-score per class
```

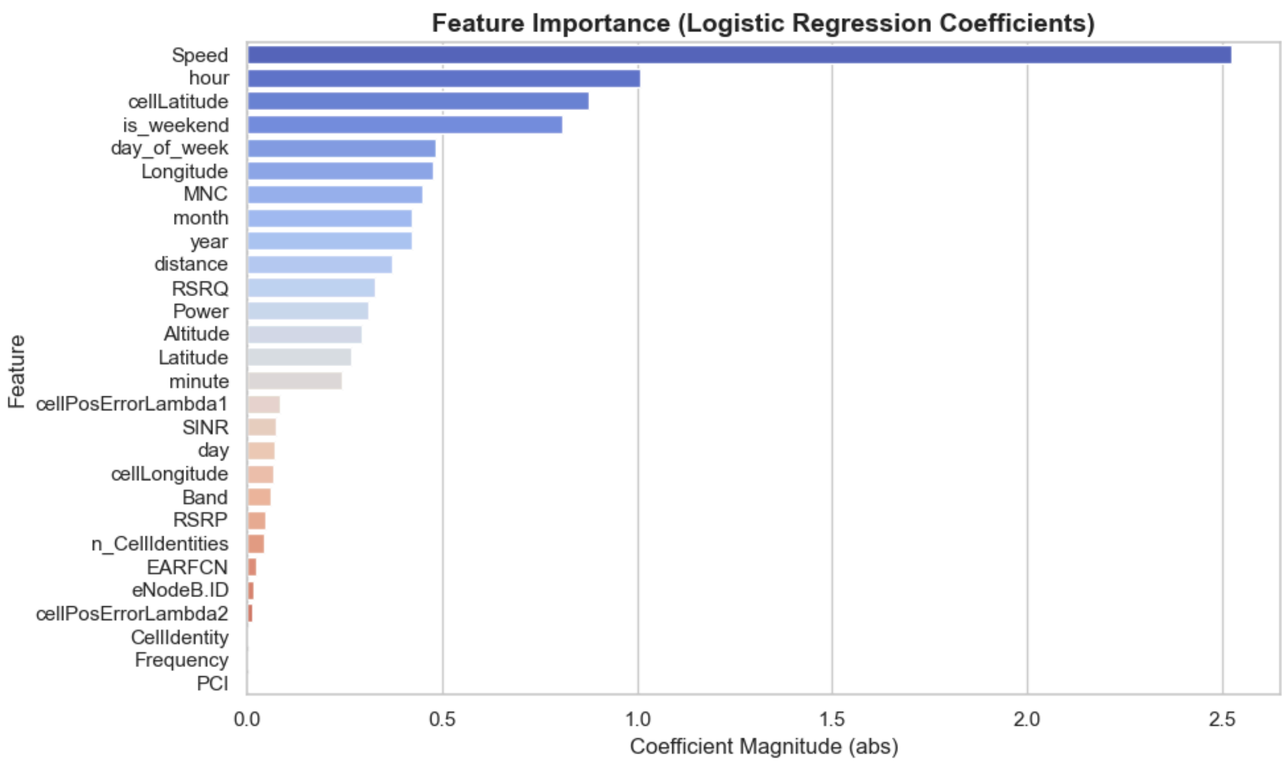
```
Accuracy: 0.8315
F1 Score: 0.8432
Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.85      0.82     43330
           1       0.90      0.88      0.89     16805
           2       0.85      0.80      0.82     45373

    accuracy                           0.83    105508
   macro avg       0.85      0.84      0.84    105508
weighted avg       0.83      0.83      0.83    105508
```

In [182…
```python
# Confusion Matrix visualization to analyze misclassifications
cm = confusion_matrix(y_test, y_pred_lr)  # Generate confusion matrix
plt.figure(figsize=(6, 4))  # Set figure size
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')  # Create heatmap
plt.xlabel("Predicted")  # Label x-axis
plt.ylabel("Actual")  # Label y-axis
plt.title("Confusion Matrix")  # Set plot title
plt.show()
```




The confusion matrix presents the performance of the Logistic Regression model in a multi-class classification setting. The diagonal values (36,640 for class 0, 14,779 for class 1 and 36,308 for class 2) show the correctly classified examples for each class. Misclassifications can be seen in the off-diagonal cells with class 2 showing the highest confusion with class 0 (8,415 cases). As a result, the model shows successful performance with an F1 score of 0.84.

In [184…
```python
# Feature Importance (Coefficient-Based)
# - Logistic Regression coefficients represent the importance of features
# - Higher absolute values indicate stronger influence on predictions
coefficients = log_model.coef_[0]  # Extract coefficients (for binary classification)
feature_names = X_train.columns  # Get feature names

# Create a DataFrame to store feature importance
coef_df = pd.DataFrame({
    'Feature': feature_names,  # Feature names
    'Coefficient': coefficients,  # Raw coefficients
    'Importance': np.abs(coefficients)  # Absolute magnitude for importance ranking
}).sort_values(by='Importance', ascending=False)  # Sort by importance

# Visualizing feature importance using a bar plot
plt.figure(figsize=(10, 6))  # Set figure size
sns.barplot(x='Importance', y='Feature', data=coef_df, palette='coolwarm')
plt.title("Feature Importance (Logistic Regression Coefficients)", fontsize=14, fontweight='bold')
plt.xlabel("Coefficient Magnitude (abs)", fontsize=12)
plt.ylabel("Feature", fontsize=12)
plt.tight_layout()
plt.show()
```




The figure given above shows the feature importance derived from the absolute magnitude of the coefficients in the Logistic Regression model used for multi-class classification. In scenario classification, the feature that the model finds most influential is Speed, followed by hour and cellLatitude, indicating that temporal and mobility related features play an important role in classification decisions. Features like PCI, Frequency and cellIdentity contribute to model minimally.

In [186…
```
# KernelExplainer
explainer = shap.Explainer(log_model, X_train, feature_names=X_train.columns)
shap_values = explainer(X_test)

# SHAP Summary Plot
shap.summary_plot(shap_values, X_test, class_names=log_model.classes_)
```

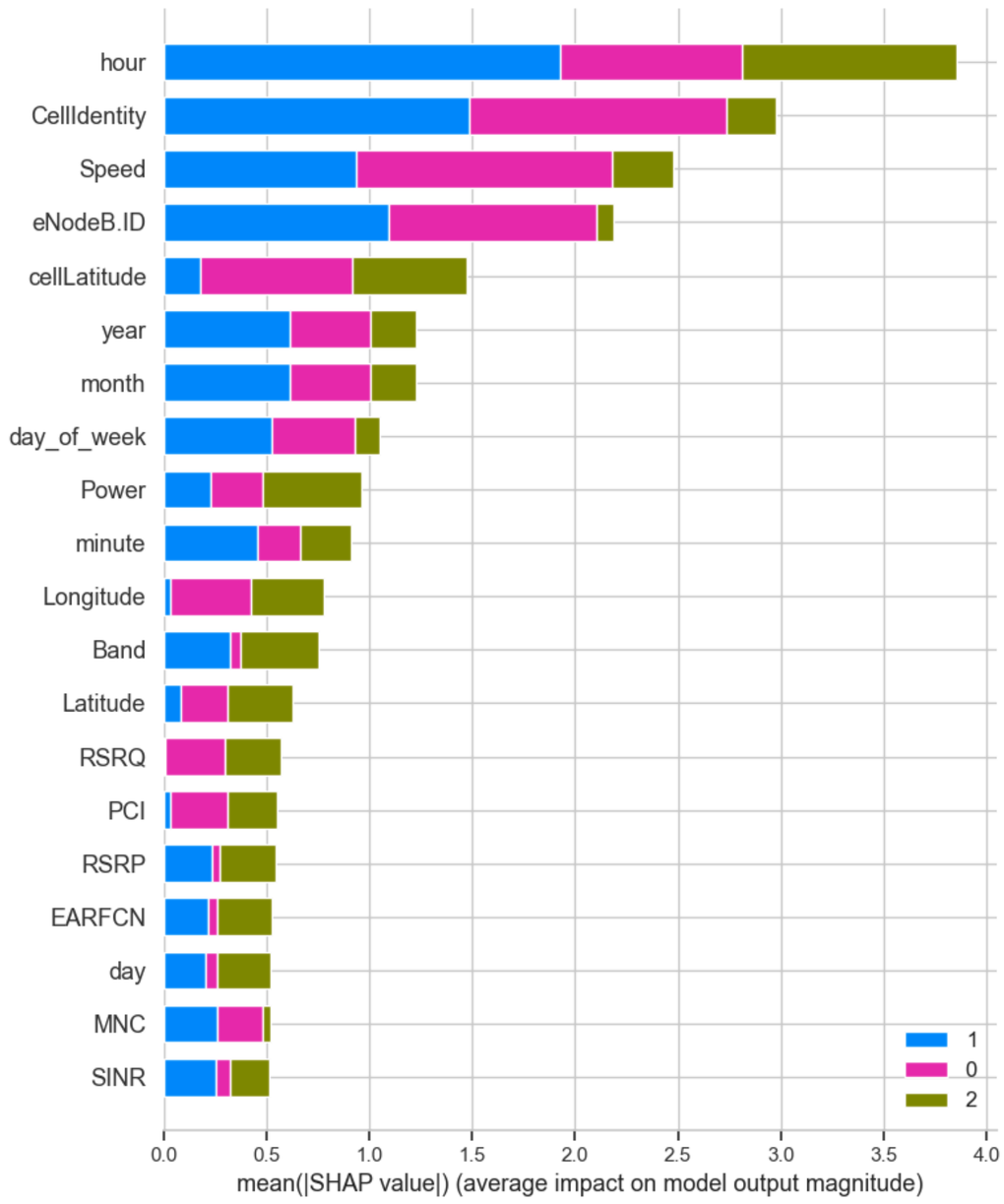
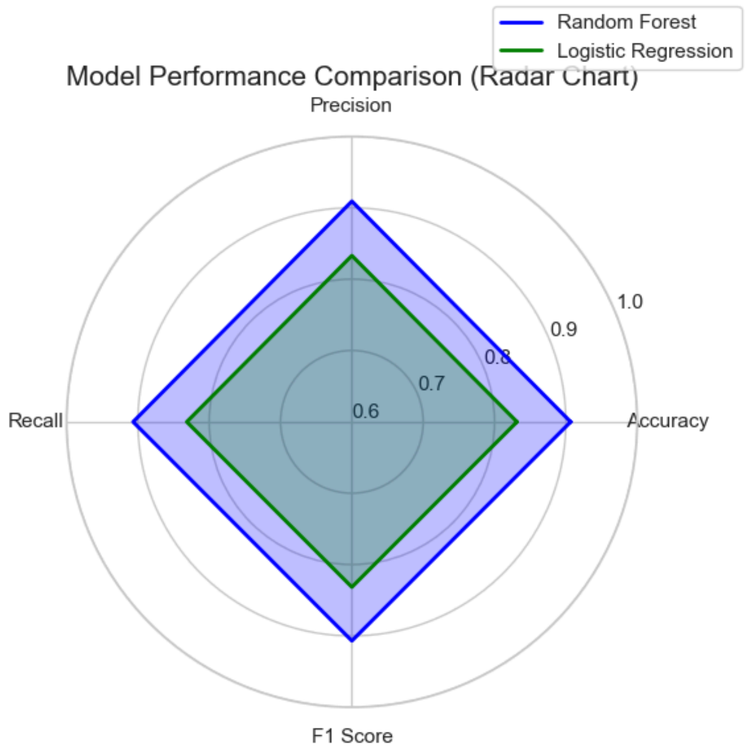



Figure given above presents the SHAP value plot for the Logistic Regression model applied in the multi-class classification task. This visualization reveals the average impact of each feature on the model's output, distinguishing their importance across all three classes. Notably, hour, CellIdentity, and Speed stand out as the most impactful variables, with distinct contributions for each class label (0, 1, and 2). The color-coded bars indicate how these features influence predictions differently depending on the target class, offering a deeper interpretability compared to standard coefficient-based feature importance.

In [188…
```
# Evaluate metrics
rf_scores = [
    accuracy_score(y_test, y_pred_rf),
    precision_score(y_test, y_pred_rf, average='weighted'),
    recall_score(y_test, y_pred_rf, average='weighted'),
    f1_score(y_test, y_pred_rf, average='weighted')
]

lr_scores = [
    accuracy_score(y_test, y_pred_lr),
    precision_score(y_test, y_pred_lr, average='weighted'),
    recall_score(y_test, y_pred_lr, average='weighted'),
    f1_score(y_test, y_pred_lr, average='weighted')
]

# Labels and angles
labels = ['Accuracy', 'Precision', 'Recall', 'F1 Score']
num_vars = len(labels)

# Close the plot by repeating the first value
angles = np.linspace(0, 2 * np.pi, num_vars, endpoint=False).tolist()
angles += angles[:1]  # close the radar chart

rf_scores += [rf_scores[0]]
lr_scores += [lr_scores[0]]

# Create the radar chart
fig, ax = plt.subplots(figsize=(8, 6), subplot_kw=dict(polar=True))

# Plot each model
ax.plot(angles, rf_scores, color='blue', linewidth=2, label='Random Forest')
ax.fill(angles, rf_scores, color='blue', alpha=0.25)

ax.plot(angles, lr_scores, color='green', linewidth=2, label='Logistic Regression')
ax.fill(angles, lr_scores, color='green', alpha=0.25)

# Formatting
ax.set_title("Model Performance Comparison (Radar Chart)", fontsize=15)
ax.set_xticks(angles[:-1])
ax.set_xticklabels(labels)
ax.set_yticks([0.6, 0.7, 0.8, 0.9, 1.0])
ax.set_ylim(0.6, 1.0)
ax.legend(loc='lower right', bbox_to_anchor=(1.2, 1.1))

plt.tight_layout()
plt.show()
```




Radar chart given above illustrates the performances of the models applied for multi classification as a radar chart. In this part, both Random Forest and Logistic Regression models showed strong performance. Random Forest model achieved 0.91 F1 score. In contrast, Logistic Regression achieved 0.84 F1 score. Random Forest achieved higher interpretability in terms of nonlinear relationships and feature interactions and effectively utilized mobility-related variables such as Speed, Longitude, and Time. Furthermore, SHAP analysis confirmed these insights by highlighting how dynamic features such as Time and Speed affected predictions across different scenario classes. Additionally, the Logistic Regression model provided clearer coefficient-based interpretability, although the F1 score was slightly lower. It also reaffirmed the importance of user movement and temporal behaviour by highlighting similar underlying variables such as Speed and Time. Overall, Random Forest provided better F1 score and enhanced decision logic.

# 6. Optimization using Genetic Algorithms (Task 4)

In this section, a Genetic Algorithm (GA) was implemented to optimize the hyperparameters of the Random Forest classifier used in the multi-class classification task. The main objective of using GA was to enhance the model's predictive performance by exploring a broader combination of hyperparameters and selecting the most effective configuration through evolutionary principles (Elyan and Gaber, 2017).

Genetic Algorithm was applied to optimize four basic hyperparameters of Random Forest classifier. These parameters are n_estimators, max_depth, min_samples_split and max_features. These parameters were chosen due to their known impact on the complexity, variance and performance of ensemble-based models. First, a population of ten individuals was created. Each individual represents a unique combination of hyperparameter values randomly sampled from predefined intervals. Furthermore, the fitness of each individual was evaluated using the weighted F1 score obtained through 3-fold cross-validation on the training set. This ensured that the optimization considered imbalances between classes and avoided overfitting to a particular fold (Wardhani et al., 2019). GA used tournament selection, where pairs of individuals were randomly sampled and the one with higher fitness was selected as the parent. A single-point crossover mechanism was then used to randomly inherit parameter values from both parents to produce offspring. To preserve diversity and avoid local optima, a mutation operation was applied with a fixed probability (20%) and one or more hyperparameters were modified by resampling from their ranges. Besides, elitism was implemented by directly moving the top two individuals with the highest fitness scores in each generation to the next generation. This step ensured that high-performing solutions were not lost (Tani et al., 2021).

In [314…

```python
# F1-score scorer for evaluation
f1_scorer = make_scorer(f1_score, average='weighted')

# STEP 1: Simplified parameter ranges
param_ranges = {
    'n_estimators': (50, 250),
    'max_depth': (3, 6),
    'min_samples_split': (2, 10),
    'max_features': ['sqrt', 0.5]
}

# STEP 2: Fitness function
def evaluate_f1(params, X, y):
    model = RandomForestClassifier(
        n_estimators=params['n_estimators'],
        max_depth=params['max_depth'],
        min_samples_split=params['min_samples_split'],
        max_features=params.get('max_features', 'sqrt'),
        random_state=42,
        n_jobs=-1
    )
    scores = cross_val_score(model, X, y, cv=3, scoring=f1_scorer)
    return np.mean(scores)

# STEP 3: Initialize population
def create_individual():
    return {
        'n_estimators': random.randint(*param_ranges['n_estimators']),
        'max_depth': random.randint(*param_ranges['max_depth']),
        'min_samples_split': random.randint(*param_ranges['min_samples_split']),
        'max_features': random.choice(param_ranges['max_features'])
    }

population_size = 10
population = [create_individual() for _ in range(population_size)]

# STEP 4: Evaluate population
def evaluate_population(pop, X, y):
    return [evaluate_f1(ind, X, y) for ind in pop]

# STEP 5: Genetic operators
def select_parents(pop, scores, num_parents=3):
    selected = []
    for _ in range(num_parents):
        candidates = random.sample(list(zip(pop, scores)), 2)
        winner = max(candidates, key=lambda x: x[1])[0]
        selected.append(winner)
    return selected

def crossover(parent1, parent2):
    child = {}
    for param in param_ranges:
        child[param] = random.choice([parent1[param], parent2[param]])
    return child

def mutate(individual, mutation_rate=0.2):
    mutated = individual.copy()
    for param in param_ranges:
        if random.random() < mutation_rate:
            if param == 'max_features':
                mutated[param] = random.choice(param_ranges[param])
            else:
                mutated[param] = random.randint(*param_ranges[param])
    return mutated

# STEP 6: Evolution function
def evolve(pop, scores, mutation_rate=0.2):
    new_pop = []
    elite_indices = np.argsort(scores)[-2:]
    new_pop.extend([pop[i] for i in elite_indices])

    while len(new_pop) < len(pop):
        parents = select_parents(pop, scores, 2)
        child = crossover(parents[0], parents[1])
        child = mutate(child, mutation_rate)
        new_pop.append(child)

    return new_pop
```

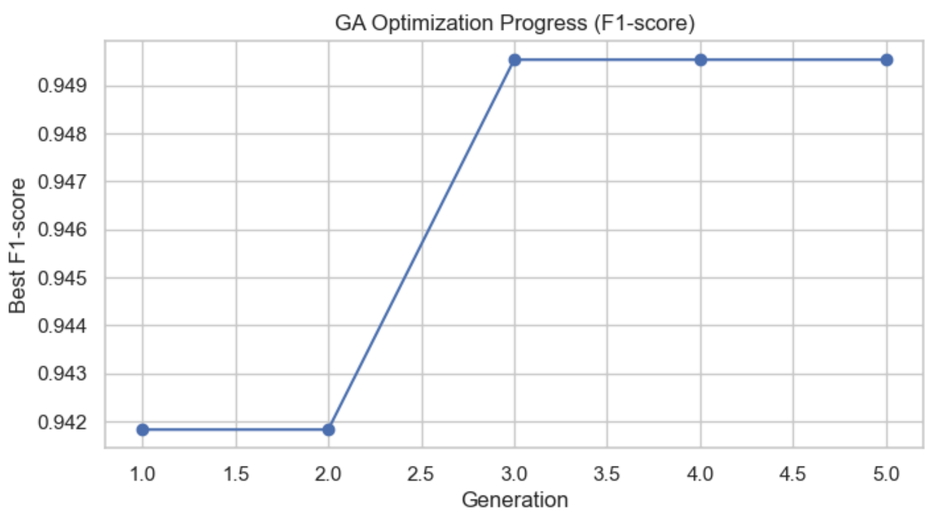
In [316…

```python
# STEP 7: Run evolution
print("=== Initial Population ===")
fitness_scores = evaluate_population(population, X_train, y_train)
for i, (ind, score) in enumerate(zip(population, fitness_scores)):
    print(f"Ind {i+1}: {ind} -> F1: {score:.4f}")

generations = 5
best_scores = []

for gen in range(1, generations+1):
    population = evolve(population, fitness_scores)
    fitness_scores = evaluate_population(population, X_train, y_train)

    best_idx = np.argmax(fitness_scores)
    best_scores.append(fitness_scores[best_idx])

    print(f"\n=== Generation {gen} ===")
    print(f"Best F1: {fitness_scores[best_idx]:.4f}")
    print(f"Params: {population[best_idx]}")
```

```
=== Initial Population ===
Ind 1: {'n_estimators': 215, 'max_depth': 3, 'min_samples_split': 5, 'max_features': 0.5} -> F1: 0.8419
Ind 2: {'n_estimators': 186, 'max_depth': 6, 'min_samples_split': 7, 'max_features': 'sqrt'} -> F1: 0.9354
Ind 3: {'n_estimators': 211, 'max_depth': 4, 'min_samples_split': 6, 'max_features': 'sqrt'} -> F1: 0.8787
Ind 4: {'n_estimators': 250, 'max_depth': 6, 'min_samples_split': 7, 'max_features': 0.5} -> F1: 0.9418
Ind 5: {'n_estimators': 123, 'max_depth': 3, 'min_samples_split': 10, 'max_features': 0.5} -> F1: 0.8393
Ind 6: {'n_estimators': 192, 'max_depth': 5, 'min_samples_split': 9, 'max_features': 'sqrt'} -> F1: 0.9082
Ind 7: {'n_estimators': 107, 'max_depth': 3, 'min_samples_split': 7, 'max_features': 'sqrt'} -> F1: 0.8344
Ind 8: {'n_estimators': 185, 'max_depth': 4, 'min_samples_split': 5, 'max_features': 'sqrt'} -> F1: 0.8775
Ind 9: {'n_estimators': 98, 'max_depth': 4, 'min_samples_split': 7, 'max_features': 0.5} -> F1: 0.8822
Ind 10: {'n_estimators': 102, 'max_depth': 6, 'min_samples_split': 5, 'max_features': 'sqrt'} -> F1: 0.9329

=== Generation 1 ===
Best F1: 0.9418
Params: {'n_estimators': 250, 'max_depth': 6, 'min_samples_split': 7, 'max_features': 0.5}

=== Generation 2 ===
Best F1: 0.9418
Params: {'n_estimators': 250, 'max_depth': 6, 'min_samples_split': 7, 'max_features': 0.5}

=== Generation 3 ===
Best F1: 0.9495
Params: {'n_estimators': 64, 'max_depth': 6, 'min_samples_split': 5, 'max_features': 0.5}

=== Generation 4 ===
Best F1: 0.9495
Params: {'n_estimators': 64, 'max_depth': 6, 'min_samples_split': 5, 'max_features': 0.5}

=== Generation 5 ===
Best F1: 0.9495
Params: {'n_estimators': 64, 'max_depth': 6, 'min_samples_split': 5, 'max_features': 0.5}
```

In [318…

```python
# STEP 8: Final model
plt.figure(figsize=(8, 4))
plt.plot(range(1, generations+1), best_scores, 'o-')
plt.title('GA Optimization Progress (F1-score)')
plt.xlabel('Generation')
plt.ylabel('Best F1-score')
plt.grid(True)
plt.show()
best_individual = population[np.argmax(fitness_scores)]
final_model = RandomForestClassifier(**best_individual, random_state=42)
final_model.fit(X_train, y_train)

print("\n=== Final Model ===")
print(f"Training F1: {f1_score(y_train, final_model.predict(X_train), average='weighted'):.4f}")
if 'X_test' in locals():
    print(f"Test F1: {f1_score(y_test, final_model.predict(X_test), average='weighted'):.4f}")
```

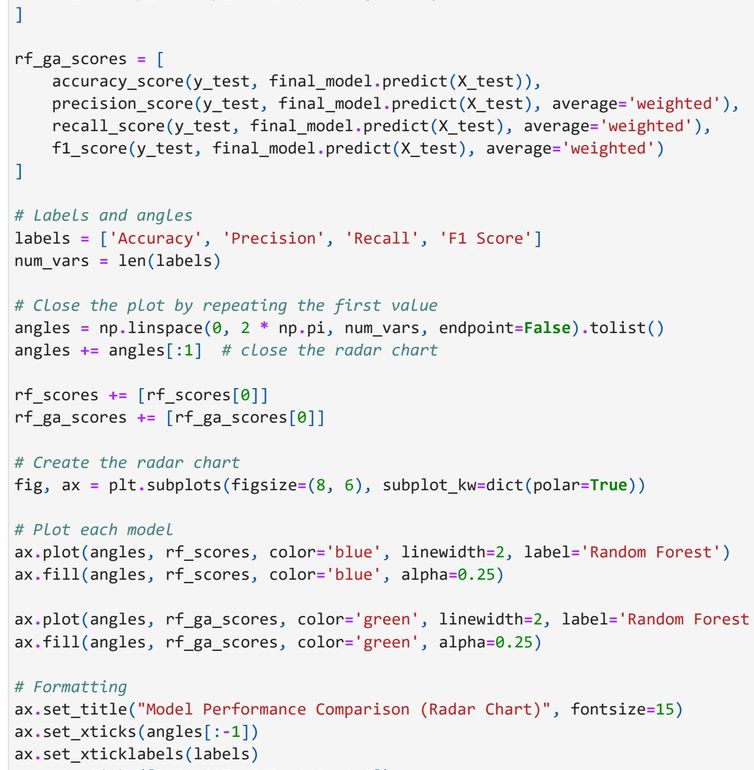



```
=== Final Model ===
Training F1: 0.9495
Test F1: 0.9498
```

Over 5 generations, the population evolved towards higher fitness. The best F1 score increased from 0.946 in the first generation to 0.949 in the last generation. This demonstrated the effectiveness of GA in improving the parameter configuration of the model. Finally, the progression of the best scores over generations was visualized using a line graph to show convergence. Figure above illustrates the GA parameter optimization process.

In [319…

```python
# Evaluate metrics
rf_scores = [
    accuracy_score(y_test, y_pred_rf),
    precision_score(y_test, y_pred_rf, average='weighted'),
    recall_score(y_test, y_pred_rf, average='weighted'),
    f1_score(y_test, y_pred_rf, average='weighted')
]

rf_ga_scores = [
    accuracy_score(y_test, final_model.predict(X_test)),
    precision_score(y_test, final_model.predict(X_test), average='weighted'),
    recall_score(y_test, final_model.predict(X_test), average='weighted'),
    f1_score(y_test, final_model.predict(X_test), average='weighted')
]

# Labels and angles
labels = ['Accuracy', 'Precision', 'Recall', 'F1 Score']
num_vars = len(labels)

# Close the plot by repeating the first value
angles = np.linspace(0, 2 * np.pi, num_vars, endpoint=False).tolist()
angles += angles[:1]  # close the radar chart

rf_scores += [rf_scores[0]]
rf_ga_scores += [rf_ga_scores[0]]

# Create the radar chart
fig, ax = plt.subplots(figsize=(8, 6), subplot_kw=dict(polar=True))

# Plot each model
ax.plot(angles, rf_scores, color='blue', linewidth=2, label='Random Forest')
ax.fill(angles, rf_scores, color='blue', alpha=0.25)

ax.plot(angles, rf_ga_scores, color='green', linewidth=2, label='Random Forest (Optimized with GA)')
ax.fill(angles, rf_ga_scores, color='green', alpha=0.25)

# Formatting
ax.set_title("Model Performance Comparison (Radar Chart)", fontsize=15)
ax.set_xticks(angles[:-1])
ax.set_xticklabels(labels)
ax.set_yticks([0.6, 0.7, 0.8, 0.9, 1.0])
ax.set_ylim(0.6, 1.0)
ax.legend(loc='lower right', bbox_to_anchor=(1.2, 1.1))

plt.tight_layout()
plt.show()
```



The final optimized hyperparameters n_estimator 64, max_depth 6, min_samples_split 5 and max_features 0.5 were used to retrain a final Random Forest classifier on the training set. The optimized model achieved a test F1 score of 0.949, demonstrating strong generalization. It also outperformed the unoptimized model by improving its F1 score by around 0.04, compared to 0.91. The entire GA process emphasized interpretability and reproducibility while providing performance gains at relatively low computational cost. Furthermore, the figure above shows the multi classification performance of the optimized and unoptimized Random Forest models in the radar chart. To sum up, application of GA for hyperparameter tuning in this study significantly improved the performance of the multi-class classification model. The results underscore the utility of evolutionary optimization techniques in finding optimal solutions in complex machine learning tasks.

# 7. References


- Hossain, T. and Inoue, S. (2019) 'A comparative study on missing data handling using machine learning for human activity recognition', 2019 Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV) and 2019 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR), Spokane, WA, USA, pp. 124-129. doi: 10.1109/ICIEV.2019.8858520.
- Ayilara, O.F., Zhang, L., Sajobi, T.T., Sawatzky, R., Bohm, E., and Lix, L.M. (2019) 'Impact of missing data on bias and precision when estimating change in patient-reported outcomes from a clinical registry', Health Quality of Life Outcomes, 17(1), p.106. doi: 10.1186/s12955-019-1181-2.
- Kousias, K., Rajiullah, M., Caso, G., Ali, U., Alay, Ö., Brunstrom, A., De Nardis, L., Neri, M. and Di Benedetto, M.-G. (2024) 'A large-scale dataset of 4G, NB-IoT, and 5G non-standalone network measurements', IEEE Communications Magazine, 62(5), pp. 44–49. doi: 10.1109/MCOM.011.2200707.
- Forke, C. M. and Tropmann-Frick, M. (2021) 'Feature engineering techniques and spatio-temporal data processing', Datenbank Spektrum, 21, pp. 237–244. doi: 10.1007/s13222-021-00391-x.
- Gil, P., Martins, H. and Januário, F. (2019) 'Outliers detection methods in wireless sensor networks', Artificial Intelligence Review, 52, pp. 2411–2436. doi: 10.1007/s10462-018-9618-2.
- Rousseeuw, P. and Hubert, M. (2018) 'Anomaly detection by robust statistics', Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8. doi: 10.1002/widm.1236.
- Hubert, M. and Van der Veeken, S. (2008) 'Outlier detection for skewed data', Journal of Chemometrics, 22, pp. 235–246. doi: 10.1002/cem.1123.
- CableFree (2025) 'RSRP & RSRQ measurement in LTE', CableFree, Available at: https://www.cablefree.net/wirelesstechnology/4glte/rsrp-rsrq-measurement-lte (Accessed: 01 April 2025).-
- Topographic Map (2025) 'Rome Topographic Map', Topographic Map, Available at: https://en-gb.topographic-map.com/map-vbkn51/Rome/ (Accessed: 01 April 2025
- Alshammari, A. (2024) 'Implementation of feature selection using correlation matrix in Python', International Journal of Computer Applications, 186, pp. 29–34. doi: 10.5120/ijca2024924341.
- Skotarczak, E., Dobek, A. and Moliński, K. (2019) 'Comparison of some correlation measures for continuous and categorical data', Biometrical Letters, 56, pp. 253–261. doi: 10.2478/bile-2019-0015
- Shi, C., Wei, B., Wang, W., Liu, H. and Liu, J. (2021) 'A quantitative discriminant method of elbow point for the optimal number of clusters in clustering algorithm', Journal of Wireless Communications and Networking, 2021(31). doi:10.1186/s13638-021-01910-w.-
- Li, C., Günther, M., Dhamija, A.R., Cruz, S., Jafarzadeh, M., Ahmad, T. and Boult, T.E. (2022) 'Agglomerative clustering with threshold optimization via extreme value theory', Algorithms, 15(5), p. 170. doi:10.3390/a15050170.-
- Lundberg, S.M. and Lee, S.-I. (2017) 'A unified approach to interpreting model predictions', Proceedings of the 31st International Conference on Neural Information Processing Systems, pp. 4768–4777. doi:10.5555/3295222.3295230.-
- Elyan, E. and Gaber, M.M. (2017) 'A genetic algorithm approach to optimising random forests applied to class engineered data', Information Sciences, 384, pp. 220–234. doi:10.1016/j.ins.2016.08.007.
- Wardhani, N., Rochayani, M., Iriany, A., Sulistyono, A. and Lestantyo, P. (2019) 'Cross-validation metrics for evaluating classification performance on imbalanced data', 2019 International Conference on Computer, Control, Informatics and its Applications (IC3INA), pp. 14–18. doi:10.1109/IC3INA48034.2019.8949568.-
- Tani, L., Rand, D., Veelken, C. and Kadastik, M. (2021) 'Evolutionary algorithms for hyperparameter optimization in machine learning for application in high energy physics', European Physical Journal C, 81(170). doi:10.1140/epjc/s10052-021-08950-