Import the dataset of 4G and Full Fibre

To depict the relationship between 4G and Full Fibre connectivity with a scatter plot, 4G and Full Fibre data are imported.

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import glob
import re
import chardet
import numpy as np
import pymongo
import folium
```

In [2]:
```
# import 4G
df4g = pd.read_csv('data/4G_2023.csv')
df4g.head()
```

Out[2]:

	laua	laua_name	AVG_4G
0	S12000033	Aberdeen City	93.60
1	S12000034	Aberdeenshire	65.64
2	E07000223	Adur	87.41
3	E07000026	Allerdale	68.39
4	E07000032	Amber Valley	87.89

In [3]:
```
# Extract the fixed broadband coverage dataset in 2023
# Read the CSV file into a DataFrame
df2023_fixed = pd.read_csv('2023J_TMA02_data/Ofcom_fixed/202305_fixed_lau
df2023_fixed.head()
```

Out[3]:

	laua	laua_name	All Premises	All Matched Premises	SFBB availability (% premises)	UFBB (100Mbit/s) availability (% premises)	avail pre
0	S12000033	ABERDEEN CITY	129315	129197	97.2	84.8	
1	S12000034	ABERDEENSHIRE	128408	128070	85.9	25.5	
2	E07000223	ADUR	29985	29953	99.1	92.8	
3	E07000026	ALLERDALE	52482	52364	93.1	6.0	
4	E07000032	AMBER VALLEY	62512	62430	97.2	62.4	

5 rows × 40 columns

In [4]:
```
# Extract 2023 from the mobile coverage and
#Full Fibre availability (% premises) from the fixed broadband coverage d
```

```
df_New2023_mobile = df4g[['laua','laua_name','AVG_4G']]

df2023_fixed = df2023_fixed[['laua','laua_name', 'Full Fibre availability

display(df_New2023_mobile.head())
display(df2023_fixed.head())
```

	laua	laua_name	AVG_4G
0	S12000033	Aberdeen City	93.60
1	S12000034	Aberdeenshire	65.64
2	E07000223	Adur	87.41
3	E07000026	Allerdale	68.39
4	E07000032	Amber Valley	87.89

	laua	laua_name	Full Fibre availability (% premises)
0	S12000033	ABERDEEN CITY	83.0
1	S12000034	ABERDEENSHIRE	25.4
2	E07000223	ADUR	65.4
3	E07000026	ALLERDALE	6.0
4	E07000032	AMBER VALLEY	59.0

In [5]:
```
# Convert 'laua_name' column in df_New2023_mobile to lowercase
df_New2023_mobile.loc[:, 'laua_name'] = df_New2023_mobile['laua_name'].st

# Convert 'laua_name' column in df2023_fixed to lowercase
df2023_fixed.loc[:, 'laua_name'] = df2023_fixed['laua_name'].str.lower()

# Merge dataframes based on 'laua' and 'laua_name'
combined_df = pd.merge(df_New2023_mobile, df2023_fixed, on=['laua', 'laua

# Display the resulting dataframe
display(combined_df.head())
```

	laua	laua_name	AVG_4G	Full Fibre availability (% premises)
0	S12000033	aberdeen city	93.60	83.0
1	S12000034	aberdeenshire	65.64	25.4
2	E07000223	adur	87.41	65.4
3	E07000026	allerdale	68.39	6.0
4	E07000032	amber valley	87.89	59.0

In [6]:
```
combined_df.shape
```

Out[6]:
```
(374, 4)
```

In [7]:
```
# Rename the '2023' column to '4G'
combined_df.rename(columns={'AVG_4G': '4G', 'Full Fibre availability (% p

# Display the DataFrame with the updated column name
display(combined_df.head())
```

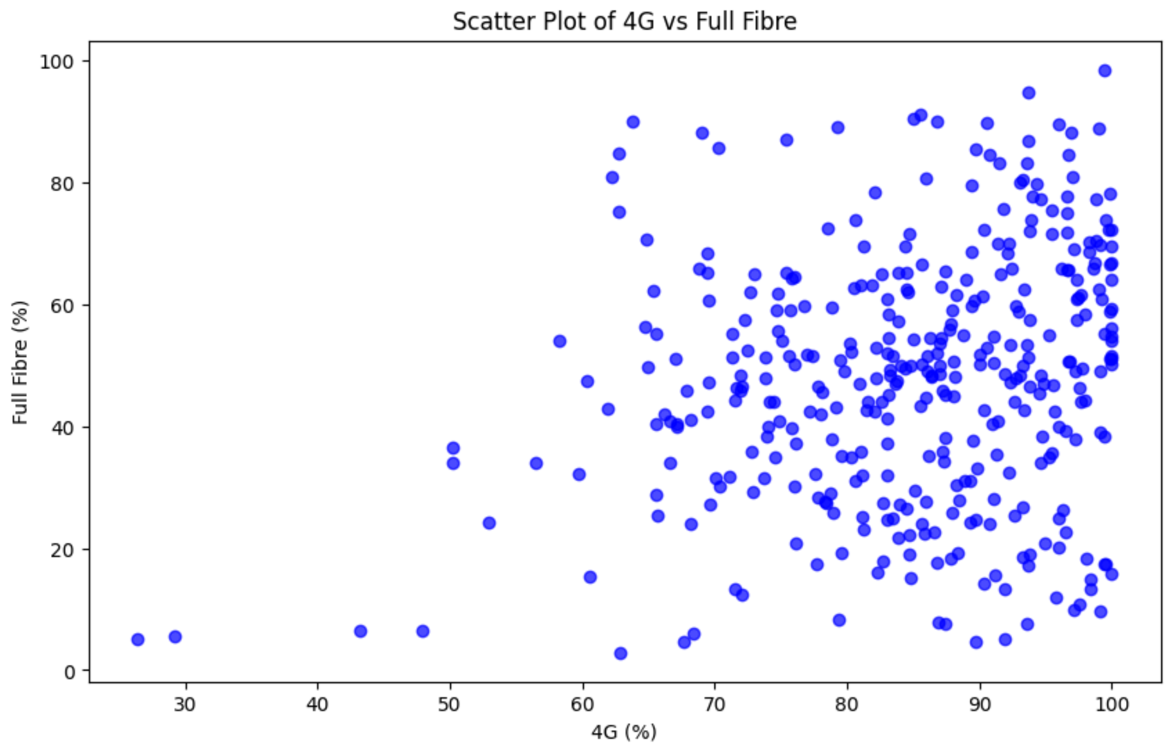
	laua	laua_name	4G	Full_Fibre
0	S12000033	aberdeen city	93.60	83.0
1	S12000034	aberdeenshire	65.64	25.4
2	E07000223	adur	87.41	65.4
3	E07000026	allerdale	68.39	6.0
4	E07000032	amber valley	87.89	59.0

Analyse the data and create the plots

In [8]:
```
# Data
laua_names = combined_df['laua_name']
four_g = combined_df['4G']
full_fibre = combined_df['Full_Fibre']

# Scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(four_g, full_fibre, color='blue', alpha=0.7)
plt.title('Scatter Plot of 4G vs Full Fibre')
plt.xlabel('4G (%)')
plt.ylabel('Full Fibre (%)')

plt.show()
```



Use K-means technique and segment the group

To analyze the connectivity between 4G and Full Fibre, data are clustered using K-means techniques.

By using statistics (percentile 25,50,75), the values to segement groups are decided.

In [9]:
```
# Calculate percentiles
percentiles = combined_df['4G'].quantile([0.25, 0.5, 0.75])

# Access individual percentiles
percentile_25 = percentiles[0.25]
median = percentiles[0.5]
percentile_75 = percentiles[0.75]

print("25th percentile:", percentile_25)
print("Median (50th percentile):", median)
print("75th percentile:", percentile_75)
```

```
25th percentile: 77.71
Median (50th percentile): 86.58
75th percentile: 93.75
```

In [10]:
```
# Calculate percentiles
percentiles = combined_df['Full_Fibre'].quantile([0.25, 0.5, 0.75])

# Access individual percentiles
percentile_25 = percentiles[0.25]
median = percentiles[0.5]
percentile_75 = percentiles[0.75]

print("25th percentile:", percentile_25)
print("Median (50th percentile):", median)
print("75th percentile:", percentile_75)
```

```
25th percentile: 32.175
Median (50th percentile): 48.45
75th percentile: 62.05
```

In [11]:
```
import pandas as pd
import numpy as np
from sklearn.neighbors import NearestNeighbors

# Drop rows with missing values
combined_df.dropna(inplace=True)

# Define initial centroids
initial_centroids = np.array([
    [94, 61],  # Centroid for "high"
    [87, 48],  # Centroid for "medium"
    [78, 32]   # Centroid for "low"
])



# Select features for segmentation
features = ['4G', 'Full_Fibre']
X = combined_df[features]
```

```
# Fit K-means model
k = 1  # Set k=1 for nearest neighbor
knn_model = NearestNeighbors(n_neighbors=k)
knn_model.fit(initial_centroids)

# Find nearest neighbors (corresponding to initial centroids)
distances, indices = knn_model.kneighbors(X)

# Assign segments based on nearest neighbors
segment_mapping = {0: 'high', 1: 'medium', 2: 'low'}
segments = [segment_mapping[idx] for idx in indices.flatten()]

# Add segment column to DataFrame
combined_df['segment'] = segments

display(combined_df)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:458: UserWarning:
X has feature names, but NearestNeighbors was fitted without feature names
  warnings.warn(
```

	laua	laua_name	4G	Full_Fibre	segment
0	S12000033	aberdeen city	93.60	83.0	high
1	S12000034	aberdeenshire	65.64	25.4	low
2	E07000223	adur	87.41	65.4	high
3	E07000026	allerdale	68.39	6.0	low
4	E07000032	amber valley	87.89	59.0	high
...	...	...	...	...	...
369	W06000006	wrexham	71.34	55.2	medium
370	E07000238	wychavon	83.28	48.4	medium
371	E07000128	wyre	83.07	60.8	high
372	E07000239	wyre forest	78.90	25.7	low
373	E06000014	york	92.40	65.9	high

373 rows × 5 columns

In [12]:
```
segment_counts = combined_df["segment"].value_counts()
print(segment_counts)
```

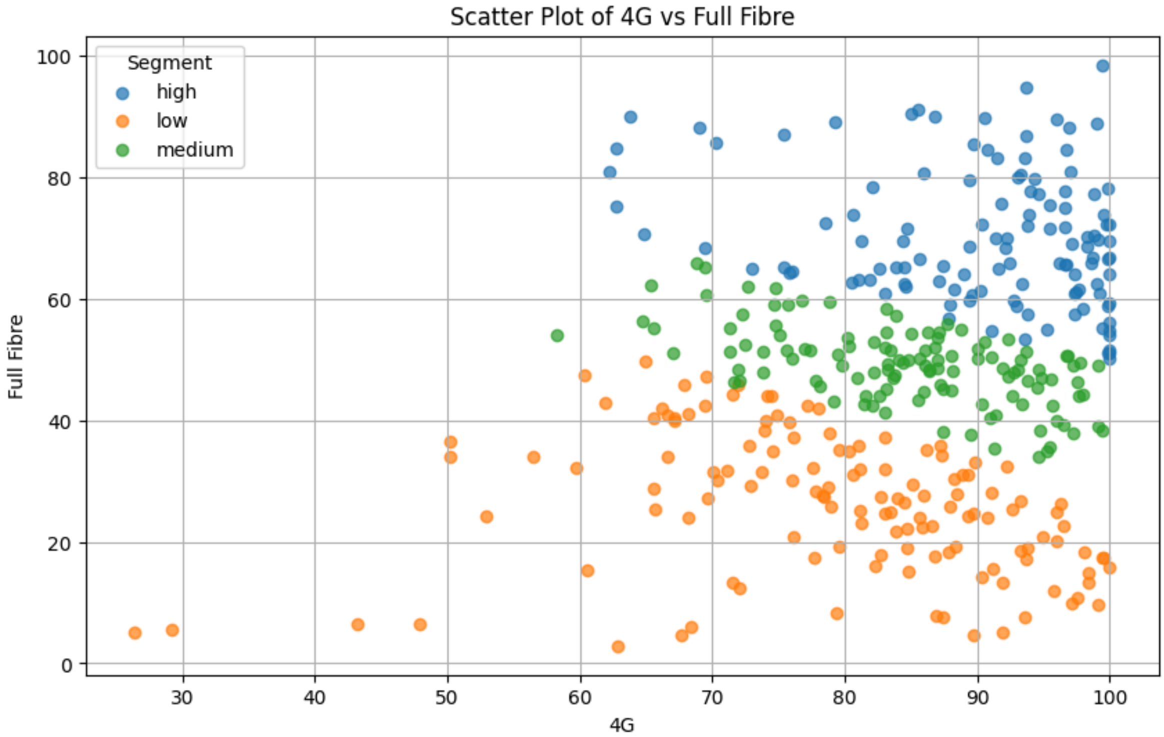
```
segment
low       132
high      121
medium    120
Name: count, dtype: int64
```

In [13]:
```
# Data
prem_4G = combined_df['4G']
full_fibre = combined_df['Full_Fibre']
segments = combined_df['segment']

# Scatter plot
```

```
plt.figure(figsize=(10, 6))
for segment in segments.unique():
    segment_data = combined_df[combined_df['segment'] == segment]
    plt.scatter(segment_data['4G'], segment_data['Full_Fibre'],
                label=segment, alpha=0.7)

plt.title('Scatter Plot of 4G vs Full Fibre')
plt.xlabel('4G')
plt.ylabel('Full Fibre')
plt.legend(title='Segment')
plt.grid(True)
plt.show()
```



Next, this segmentation is visualised on a map to see how different the connectivity between 4G and Full Fibre in 2023 was.

In [14]:
```
# Use geojson data to visualise maps
import geopandas as gpd

geojson_path = '2023J_TMA02_data/Boundaries/Local_Authority_Districts_Dec
geojson_data = gpd.read_file(geojson_path)
```

In [15]:
```
# Combine dfNew2023 with geojson_data

# Convert both columns to lowercase before merging
geojson_data['LAD22NM'] = geojson_data['LAD22NM'].str.lower()
combined_df['laua_name'] = combined_df['laua_name'].str.lower()

# Use .loc to avoid SettingWithCopyWarning
combined_df.loc[:, 'laua_name'] = combined_df['laua_name'].str.lower()

# Merge the DataFrames on the lowercase columns
df_combined_geo_1 = pd.merge(geojson_data, combined_df, left_on='LAD22NM'

# Drop the temporary lowercase columns
df_combined_geo_1 = df_combined_geo_1.drop(columns=['LAD22NM'])
```

```python
# Display the resulting DataFrame
display(df_combined_geo_1.head())
```

	FID	LAD22CD	BNG_E	BNG_N	LONG	LAT	GlobalID	geor
0	339	S12000033	387763	808479	-2.20398	57.16697	bc868205-08c7-47a9-88af-6cf72d57fbc8	MULTIPOL' (((-2.0 57.0 -2.0803
1	340	S12000034	352284	816277	-2.79208	57.23469	e9d43203-2a53-46ca-a3a6-762a33027034	MULTIPOL' (((-1.8 57.4 -1.8345
2	221	E07000223	518076	106472	-0.32417	50.84572	d56eedd2-29d2-40f8-a6b8-5f0b952ba9a4	POL' ((-0.2 50.8 -0.2 50.82
3	65	E07000026	317520	532997	-3.28090	54.68524	e6e9b854-1a61-4f46-928c-8ca3a83edbfc	POL' ((-3.1 54.9 -3.1 54.90
4	71	E07000032	436166	348084	-1.46219	53.02884	2ff039cf-0a31-4ac2-a02a-beca575e827c	POL' ((-1.3 53.1 -1.3 53.09

In [16]:
```python
# Mapping dictionary
segment_mapping = {
    'low': 1,
    'medium': 2,
    'high': 3
}

# Create 'segment_2' column based on the 'segment' column
df_combined_geo_1['segment_2'] = df_combined_geo_1['segment'].map(segment

# Display the updated DataFrame
display(df_combined_geo_1.head())
```

	FID	LAD22CD	BNG_E	BNG_N	LONG	LAT	GlobalID	geor
0	339	S12000033	387763	808479	-2.20398	57.16697	bc868205-08c7-47a9-88af-6cf72d57fbc8	MULTIPOL' (((-2.0 57.0 -2.0803:
1	340	S12000034	352284	816277	-2.79208	57.23469	e9d43203-2a53-46ca-a3a6-762a33027034	MULTIPOL' (((-1.8 57.4 -1.8345(
2	221	E07000223	518076	106472	-0.32417	50.84572	d56eedd2-29d2-40f8-a6b8-5f0b952ba9a4	POL' ((-0.2 50.8 -0.2 50.82
3	65	E07000026	317520	532997	-3.28090	54.68524	e6e9b854-1a61-4f46-928c-8ca3a83edbfc	POL' ((-3. 54.9 -3.' 54.90
4	71	E07000032	436166	348084	-1.46219	53.02884	2ff039cf-0a31-4ac2-a02a-beca575e827c	POL' ((-1.3 53.1 -1.3 53.09

In [17]:
```
#Check the null values
df_combined_geo_1.isnull().sum()
```

Out[17]:
```
FID            0
LAD22CD        0
BNG_E          0
BNG_N          0
LONG           0
LAT            0
GlobalID       0
geometry       0
laua           0
laua_name      0
4G             0
Full_Fibre     0
segment        0
segment_2      0
dtype: int64
```

In [18]:
```
gdf = gpd.GeoDataFrame(df_combined_geo_1, geometry='geometry')

# Create a base map
m = folium.Map(location=[54.5, -2], zoom_start=6)  # Centered on the UK

# Define a function to get the color for each segment
def get_color(segment):
    if segment == 1:
        return 'blue'
    elif segment == 2:
        return 'green'
    elif segment == 3:
```

```
            return 'red'
        else:
            return 'gray'

# Add GeoJSON to the map
folium.GeoJson(
    gdf,
    style_function=lambda feature: {
        'fillColor': get_color(feature['properties']['segment_2']),
        'color': 'black',
        'weight': 1,
        'fillOpacity': 0.6,
    }
).add_to(m)

# Add a legend
legend_html = '''
<div style="position: fixed;
            bottom: 50px; left: 50px; width: 150px; height: 100px;
            border:2px solid grey; z-index:9999; font-size:14px;">
      <b>Segments</b> <br>
      Low   <i class="fa fa-square" style="color:blue"></i><br>
      Medium   <i class="fa fa-square" style="color:green"></i>
      High   <i class="fa fa-square" style="color:red"></i><br>
</div>
'''

m.get_root().html.add_child(folium.Element(legend_html))

m
```

Out[18]: Make this Notebook Trusted to load map: File -> Trust Notebook

Segments
Low ■
Medium ■
High ■

Northern Ireland made significant contributions to the advancement of 4G and full-fibre networks, with all areas categorised as highly advanced. Similarly, regions with large cities, such as London, also exhibited high performance in both areas. In contrast, Scotland showed comparatively lower performance in these advancements.

Add the information about nation

The investigation into whether there are any patterns by nation in the association between 4G and Full Fibre is conducted by visualising a scatter plot with the legend indicating the nation.

In [19]:

```
# Add the information of nations
# Mapping dictionary for LAD22CD to nation
lad_to_nation = {
    'E': 'England',
    'N': 'Northern Ireland',
    'S': 'Scotland',
    'W': 'Wales'
}

# Create a new 'nation' column based on 'LAD22CD'
geojson_data['nation'] = geojson_data['LAD22CD'].str[0].map(lad_to_nation

# Print the updated DataFrame
print(geojson_data[['LAD22CD', 'nation']])
```

```
       LAD22CD   nation
0    E06000001  England
1    E06000002  England
2    E06000003  England
3    E06000004  England
4    E06000005  England
..         ...      ...
369  W06000020    Wales
370  W06000021    Wales
371  W06000022    Wales
372  W06000023    Wales
373  W06000024    Wales

[374 rows x 2 columns]
```

In [20]:

```
geojson_data_1 = geojson_data[['LAD22CD', 'nation']]
display(geojson_data_1)
```

	LAD22CD	nation
0	E06000001	England
1	E06000002	England
2	E06000003	England
3	E06000004	England
4	E06000005	England
...	...	...
369	W06000020	Wales
370	W06000021	Wales
371	W06000022	Wales
372	W06000023	Wales
373	W06000024	Wales

374 rows × 2 columns

In [21]:
```
# Merging merged_df and geojson_data_1 on 'laua' and 'LAD22CD'
merged_nation = pd.merge(df_combined_geo_1, geojson_data_1, left_on='laua

display(merged_nation.head())
```

	FID	LAD22CD_x	BNG_E	BNG_N	LONG	LAT	GlobalID	geo
0	339	S12000033	387763	808479	-2.20398	57.16697	bc868205-08c7-47a9-88af-6cf72d57fbc8	MULTIPOI (((-2. 57.(-2.080
1	340	S12000034	352284	816277	-2.79208	57.23469	e9d43203-2a53-46ca-a3a6-762a33027034	MULTIPOI (((-1 57. -1.834
2	221	E07000223	518076	106472	-0.32417	50.84572	d56eedd2-29d2-40f8-a6b8-5f0b952ba9a4	POI ((-0. 50.8 -0 50.8
3	65	E07000026	317520	532997	-3.28090	54.68524	e6e9b854-1a61-4f46-928c-8ca3a83edbfc	POI ((-3 54. -3 54.9
4	71	E07000032	436166	348084	-1.46219	53.02884	2ff039cf-0a31-4ac2-a02a-beca575e827c	POI ((-1. 53. -1 53.0

In [22]:
```
# Data
laua_names = merged_nation['laua_name']
```

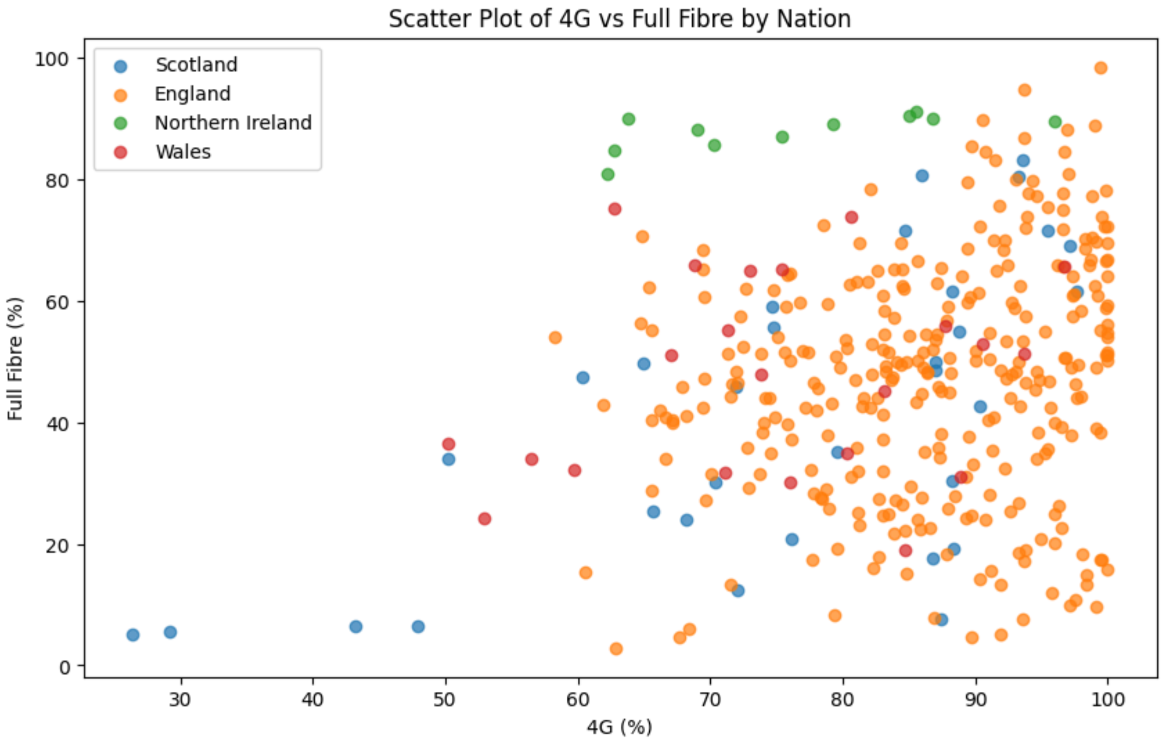
```
four_g = merged_nation['4G']
full_fibre = merged_nation['Full_Fibre']
nations = merged_nation['nation']

# Scatter plot
plt.figure(figsize=(10, 6))
for nation in nations.unique():
    plt.scatter(four_g[nations == nation], full_fibre[nations == nation],

# Set plot title and labels
plt.title('Scatter Plot of 4G vs Full Fibre by Nation')
plt.xlabel('4G (%)')
plt.ylabel('Full Fibre (%)')

# Add legend
plt.legend()

plt.show()
```



It is noticeable that all areas of Northern Ireland have high performance in full-fibre connectivity, with varying levels of 4G advancement. In contrast, some areas of Scotland show significantly lower performance in both full-fibre and 4G. In England and Wales, 4G coverage is relatively high (over 60%), but full-fibre availability varies widely, ranging from 0 to 100%.

4G and Full Fibre For 5 years

The advancement of 4G and Full Fibre by nation for 5 years is investigated.

In [23]:
```
MONGO_CONNECTION_STRING = f"mongodb://localhost:27017/"
```

In [24]:
```
from pymongo import MongoClient
mongo_client = MongoClient(MONGO_CONNECTION_STRING)
```

```
DB_NAME = "Q1_TMA02_TM351"
print(f"DB_NAME = {DB_NAME}")

mongo_db = mongo_client[DB_NAME]
```

DB_NAME = Q1_TMA02_TM351

In [25]:

```
import geopandas as gpd

geojson_path = '2023J_TMA02_data/Boundaries/Local_Authority_Districts_Dec
geojson_data = gpd.read_file(geojson_path)
```

In [26]:

```
from pymongo import MongoClient
import pandas as pd

# Connect to MongoDB
MONGO_CONNECTION_STRING = "mongodb://localhost:27017/"
mongo_client = MongoClient(MONGO_CONNECTION_STRING)
DB_NAME = "Q1_TMA02_TM351"
mongo_db = mongo_client[DB_NAME]

# List collections
collections = mongo_db.list_collection_names()
print(f"Collections in database '{DB_NAME}': {collections}")

# Initialize an empty DataFrame to hold combined data
df_combined = pd.DataFrame()

# Loop through the actual collection names
for collection_name in collections:
    # Fetch data from MongoDB for the specified collection
    data = list(mongo_db[collection_name].find({}, {'_id': 0, 'laua': 1,

    # Check if there is data in the collection
    if data:
        # Add the data to the DataFrame
        df_combined = pd.concat([df_combined, pd.DataFrame(data)])
    else:
        print(f"No data found in collection: {collection_name}")

# Display the combined DataFrame
display(df_combined)
```

```
Collections in database 'Q1_TMA02_TM351': ['data_2019', 'data_2020', 'data
_2023', 'data_2021', 'data_2022']
```

	laua	laua_name	Full Fibre availability (% premises)	year
0	S12000033	ABERDEEN CITY	13.1	2019
1	S12000034	ABERDEENSHIRE	2.7	2019
2	E07000223	ADUR	0.6	2019
3	E07000026	ALLERDALE	1.7	2019
4	E07000032	AMBER VALLEY	22.1	2019
...	...	...	...	...
369	W06000006	WREXHAM	47.6	2022
370	E07000238	WYCHAVON	29.4	2022
371	E07000128	WYRE	60.2	2022
372	E07000239	WYRE FOREST	10.3	2022
373	E06000014	YORK	52.3	2022

1883 rows × 4 columns

In [27]:
```
# chack the number of rows by year
df_combined['year'].value_counts()
```

Out[27]:
```
year
2019    382
2020    379
2023    374
2021    374
2022    374
Name: count, dtype: int64
```

Add the information about nation

In [28]:
```
# Mapping dictionary for LAD22CD to nation
lad_to_nation = {
    'E': 'England',
    'N': 'Northern Ireland',
    'S': 'Scotland',
    'W': 'Wales'
}

# Create a new 'nation' column based on 'LAD22CD'
geojson_data['nation'] = geojson_data['LAD22CD'].str[0].map(lad_to_nation

# Print the updated DataFrame
print(geojson_data[['LAD22CD', 'nation']])
```

```
       LAD22CD   nation
0    E06000001  England
1    E06000002  England
2    E06000003  England
3    E06000004  England
4    E06000005  England
..         ...      ...
369  W06000020    Wales
370  W06000021    Wales
371  W06000022    Wales
372  W06000023    Wales
373  W06000024    Wales

[374 rows x 2 columns]
```

In [29]:
```
geojson_data_1 = geojson_data[['LAD22CD', 'nation']]
display(geojson_data_1)
```

	LAD22CD	nation
0	E06000001	England
1	E06000002	England
2	E06000003	England
3	E06000004	England
4	E06000005	England
...	...	...
369	W06000020	Wales
370	W06000021	Wales
371	W06000022	Wales
372	W06000023	Wales
373	W06000024	Wales

374 rows × 2 columns

In [30]:
```
# Merging merged_df and geojson_data_1 on 'laua' and 'LAD22CD'
full_fibre = pd.merge(df_combined, geojson_data_1, left_on='laua', right_

display(full_fibre)
```

	laua	laua_name	Full Fibre availability (% premises)	year	LAD22CD	nation
0	S12000033	ABERDEEN CITY	13.1	2019	S12000033	Scotland
1	S12000033	ABERDEEN CITY	34.9	2020	S12000033	Scotland
2	S12000033	ABERDEEN CITY	83.0	2023	S12000033	Scotland
3	S12000033	ABERDEEN CITY	58.4	2021	S12000033	Scotland
4	S12000033	ABERDEEN CITY	74.4	2022	S12000033	Scotland
...	...	...	...	...	...	...
1860	E06000061	NORTH NORTHAMPTONSHIRE	21.6	2021	E06000061	England
1861	E06000061	NORTH NORTHAMPTONSHIRE	34.8	2022	E06000061	England
1862	E06000062	WEST NORTHAMPTONSHIRE	85.3	2023	E06000062	England
1863	E06000062	WEST NORTHAMPTONSHIRE	41.5	2021	E06000062	England
1864	E06000062	WEST NORTHAMPTONSHIRE	72.9	2022	E06000062	England

1865 rows × 6 columns

Create the data by nation

In [31]:

```
# Group by 'nation' and 'year' and calculate the mean of 'Full Fibre avai
grouped_data = full_fibre.groupby(['nation', 'year'])['Full Fibre availab

# Display the grouped data
display(grouped_data)
```

	nation	year	Full Fibre availability (% premises)
0	England	2019	8.10
1	England	2020	13.71
2	England	2021	22.57
3	England	2022	37.15
4	England	2023	46.90
5	Northern Ireland	2019	26.37
6	Northern Ireland	2020	50.79
7	Northern Ireland	2021	66.85
8	Northern Ireland	2022	82.70
9	Northern Ireland	2023	87.82
10	Scotland	2019	5.93
11	Scotland	2020	13.43
12	Scotland	2021	22.29
13	Scotland	2022	34.28
14	Scotland	2023	41.01
15	Wales	2019	10.08
16	Wales	2020	15.72
17	Wales	2021	24.45
18	Wales	2022	36.54
19	Wales	2023	47.42

In [32]:
```
grouped_data = grouped_data.rename(columns={'Full Fibre availability (% p

# Display the grouped data
display(grouped_data)
```

	nation	year	Full_Fibre
0	England	2019	8.10
1	England	2020	13.71
2	England	2021	22.57
3	England	2022	37.15
4	England	2023	46.90
5	Northern Ireland	2019	26.37
6	Northern Ireland	2020	50.79
7	Northern Ireland	2021	66.85
8	Northern Ireland	2022	82.70
9	Northern Ireland	2023	87.82
10	Scotland	2019	5.93
11	Scotland	2020	13.43
12	Scotland	2021	22.29
13	Scotland	2022	34.28
14	Scotland	2023	41.01
15	Wales	2019	10.08
16	Wales	2020	15.72
17	Wales	2021	24.45
18	Wales	2022	36.54
19	Wales	2023	47.42

In [33]:

```
# Load the data
nation_4G = pd.read_csv('data/4G_nation.csv')
nation_4G.head()
```

Out[33]:

	nation	2019	2020	2021	2022	2023
0	England	78.22	82.72	83.69	85.29	86.37
1	Northern Ireland	69.45	74.12	74.48	78.49	79.36
2	Scotland	67.47	74.24	75.13	76.92	78.04
3	Wales	65.50	72.31	73.10	73.93	75.57

In [34]:

```
# Reshape the DataFrame using melt
melted_data = nation_4G.melt(id_vars='nation', var_name='year', value_nam

# Display the reshaped DataFrame
display(melted_data)
```

	nation	year	4G
0	England	2019	78.22
1	Northern Ireland	2019	69.45
2	Scotland	2019	67.47
3	Wales	2019	65.50
4	England	2020	82.72
5	Northern Ireland	2020	74.12
6	Scotland	2020	74.24
7	Wales	2020	72.31
8	England	2021	83.69
9	Northern Ireland	2021	74.48
10	Scotland	2021	75.13
11	Wales	2021	73.10
12	England	2022	85.29
13	Northern Ireland	2022	78.49
14	Scotland	2022	76.92
15	Wales	2022	73.93
16	England	2023	86.37
17	Northern Ireland	2023	79.36
18	Scotland	2023	78.04
19	Wales	2023	75.57

In [35]:
```
# Check the type
melted_data.dtypes
```

Out[35]:
```
nation     object
year       object
4G        float64
dtype: object
```

In [36]:
```
# Year has to be integer. Therefore, Convert the 'year' column to int64
melted_data['year'] = melted_data['year'].astype('int64')

# Display the updated melted_data DataFrame
display(melted_data)
```

	nation	year	4G
0	England	2019	78.22
1	Northern Ireland	2019	69.45
2	Scotland	2019	67.47
3	Wales	2019	65.50
4	England	2020	82.72
5	Northern Ireland	2020	74.12
6	Scotland	2020	74.24
7	Wales	2020	72.31
8	England	2021	83.69
9	Northern Ireland	2021	74.48
10	Scotland	2021	75.13
11	Wales	2021	73.10
12	England	2022	85.29
13	Northern Ireland	2022	78.49
14	Scotland	2022	76.92
15	Wales	2022	73.93
16	England	2023	86.37
17	Northern Ireland	2023	79.36
18	Scotland	2023	78.04
19	Wales	2023	75.57

In [37]:

```
# Merge grouped_data and melted_data on 'nation' and 'year'
merge_df = pd.merge(grouped_data, melted_data, on=['nation', 'year'])

# Display the merged DataFrame
display(merge_df)
```

	nation	year	Full_Fibre	4G
0	England	2019	8.10	78.22
1	England	2020	13.71	82.72
2	England	2021	22.57	83.69
3	England	2022	37.15	85.29
4	England	2023	46.90	86.37
5	Northern Ireland	2019	26.37	69.45
6	Northern Ireland	2020	50.79	74.12
7	Northern Ireland	2021	66.85	74.48
8	Northern Ireland	2022	82.70	78.49
9	Northern Ireland	2023	87.82	79.36
10	Scotland	2019	5.93	67.47
11	Scotland	2020	13.43	74.24
12	Scotland	2021	22.29	75.13
13	Scotland	2022	34.28	76.92
14	Scotland	2023	41.01	78.04
15	Wales	2019	10.08	65.50
16	Wales	2020	15.72	72.31
17	Wales	2021	24.45	73.10
18	Wales	2022	36.54	73.93
19	Wales	2023	47.42	75.57

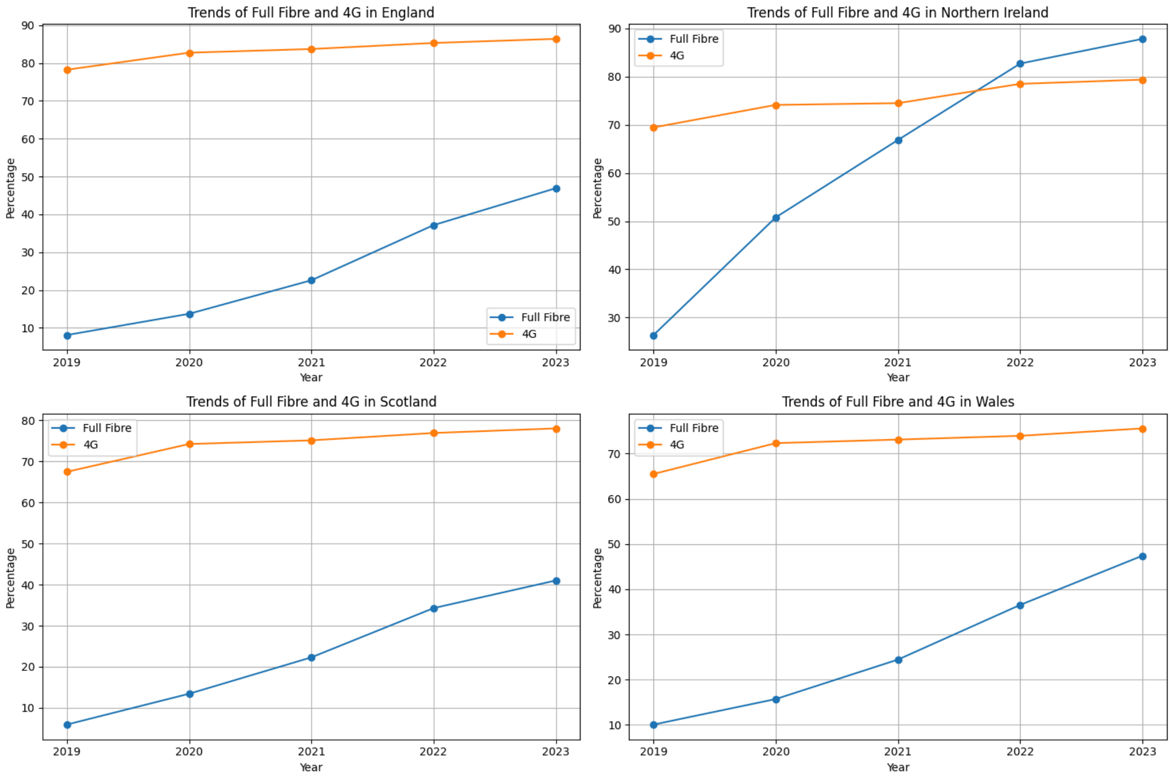
In [38]:

```
# Get unique nations
unique_nations = merge_df['nation'].unique()

# Create subplots
fig, axs = plt.subplots(2, 2, figsize=(15, 10))

# Iterate over each nation and create a separate bar chart
for i, nation in enumerate(unique_nations):
    ax = axs[i // 2, i % 2]
    nation_data = merge_df[merge_df['nation'] == nation]
    ax.plot(nation_data['year'], nation_data['Full_Fibre'], marker='o', l
    ax.plot(nation_data['year'], nation_data['4G'], marker='o', label='4G
    ax.set_title(f'Trends of Full Fibre and 4G in {nation}')
    ax.set_xlabel('Year')
    ax.set_ylabel('Percentage')
    ax.set_xticks(nation_data['year'])
    ax.legend()
    ax.grid(True)

# Adjust layout
plt.tight_layout()
plt.show()
```



Except for Northern Ireland, similar trends were observed over the five-year period for all nations. 4G availability consistently contributed over 65%, showing a gradual increase each year. In contrast, Full Fibre availability in Northern Ireland experienced a dramatic rise, surpassing 4G percentages in 2022 and nearly reaching 90% by 2023. However, other nations saw slower growth in Full Fibre adoption, starting around 10% in 2019 and not reaching 50% by 2023.

In [39]:
```
# save the data
#merge_df.to_csv('4g_full_fibre_nation.csv', index=False)
```

In [ ]:
```
```