Partitioning Techniques in AI Models for Wireless Network Optimization

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Part 2: Practical Implementation

We need to apply **vertical** and **horizontal partitioning** techniques to AI models to **predict network latency** in wireless communication systems. The dataset contains **tower and user attributes**, and we will analyze how these partitioning strategies affect the model's:

- **Performance**
- **Scalability**
- **Practical deployment**

In this section, we will apply the concepts of vertical and horizontal partitioning to build, train, and evaluate models using wireless network datasets.

We will:

- **Prepare the dataset.**
- **Implement baseline models.**
- **Apply vertical and horizontal partitioning.**
- **Evaluate and compare performance across all strategies.**

Import Required Libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import MinMaxScaler
```

Load and Preprocess Dataset

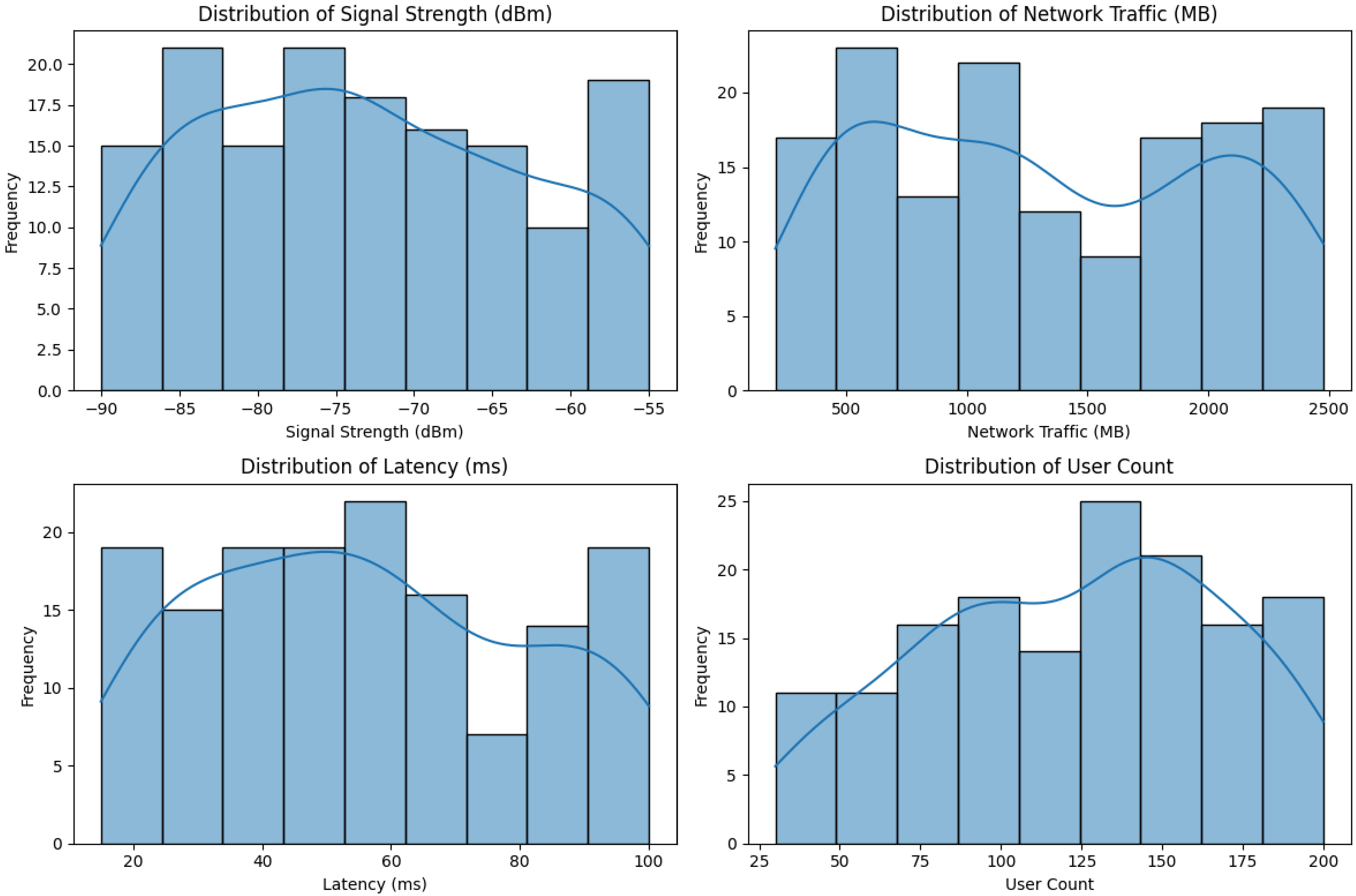
In [2]:
```python
# Load dataset
data = pd.read_excel('partitioning_dataset.xlsx')

print("Shape of the dataset:", data.shape)
data.head()
```

```
Shape of the dataset: (150, 7)
```

Out[2]:

	Tower ID	Signal Strength (dBm)	Network Traffic (MB)	Latency (ms)	User Count	Device Type	Location Type
0	TWR001	-83	522	59	106	IoT Device	Rural
1	TWR002	-89	550	23	159	Laptop	Rural
2	TWR003	-73	2190	46	109	IoT Device	Rural
3	TWR004	-75	483	62	200	Tablet	Rural
4	TWR005	-76	2381	51	134	IoT Device	Rural

In [3]:
```python
numerical_cols = ['Signal Strength (dBm)', 'Network Traffic (MB)', 'Latency (ms)', 'User Count']

fig, axes = plt.subplots(2, 2, figsize=(12, 8))
axes = axes.flatten()

for i, col in enumerate(numerical_cols):
    sns.histplot(data[col], kde=True, ax=axes[i])
    axes[i].set_title(f'Distribution of {col}')
    axes[i].set_xlabel(col)
    axes[i].set_ylabel('Frequency')

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



A. Vertical Partitioning

In this section, we explore vertical partitioning by splitting the features into two distinct groups: **infrastructure-related** and **user-related** attributes.

We will:

- Separate the dataset into two views: **infrastructure features** (`Signal Strength` , `Network Traffic`) and **user features** (`User Count` , `Device Type`).
- Train individual models on each feature group.

- Combine predictions using **fusion** techniques:
  - Stacking with a meta-model (e.g., Linear Regression, XGBoost)
- Compare the **fused model's** performance against a **baseline monolithic model** trained on all features together.

Preprocess Dataset

In [4]:
```
# Drop non-predictive columns
data_cleaned = data.drop(columns=['Tower ID', 'Location Type'])

# Define feature groups
features_infra = ['Signal Strength (dBm)', 'Network Traffic (MB)']
features_user = ['User Count', 'Device Type']
target = 'Latency (ms)'

# Split features and target
X_infra = data_cleaned[features_infra]
X_user = data_cleaned[features_user]
y = data_cleaned[target]
```

Train-Test Splitting

In [5]:
```
# Split data into train+val and test (80/20)
X_infra_trainval, X_infra_test, X_user_trainval, X_user_test, y_trainval, y_test = train_test_split(
    X_infra, X_user, y, test_size=0.2, random_state=42
)
```

In [6]:
```
# Further split train+val into train and val (60/20/20 total split)
X_infra_train, X_infra_val, X_user_train, X_user_val, y_train, y_val = train_test_split(
    X_infra_trainval, X_user_trainval, y_trainval, test_size=0.25, random_state=42
)
```

Define Sub-model Pipelines

Infrastructure Model Pipeline:

In [7]:
```
model_infra = Pipeline([
    ('scaler', StandardScaler()),
    ('regressor', RandomForestRegressor(n_estimators=100, random_state=42))
])
```

User Behavior Model Pipeline (handles categorical data):

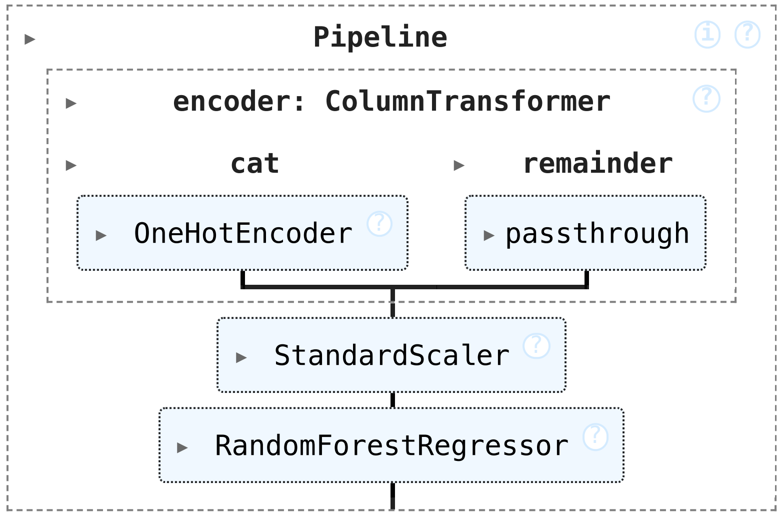
In [8]:
```
# Define encoder for user features
encoder = ColumnTransformer(
    transformers=[('cat', OneHotEncoder(), ['Device Type'])],
    remainder='passthrough',
    force_int_remainder_cols=False
)

model_user = Pipeline([
    ('encoder', encoder),
```

```
    ('scaler', StandardScaler(with_mean=False)),
    ('regressor', RandomForestRegressor(n_estimators=100, random_state=42))
])
```

Train Both Sub-models

In [9]:
```
model_infra.fit(X_infra_train, y_train)
model_user.fit(X_user_train, y_train)
```

Out[9]:



Generate Predictions and Fuse Outputs

In [10]:
```
# Individual predictions
infra_val_preds = model_infra.predict(X_infra_val)
user_val_preds = model_user.predict(X_user_val)
X_stack_train = np.column_stack((infra_val_preds, user_val_preds))
y_stack_train = y_val
```

Fusion of Sub-Model Predictions

What is Prediction Fusion?

Prediction fusion is the process of combining the outputs of multiple models to generate a **single, more accurate prediction**. This is particularly useful when individual models are trained on **different feature sets** (e.g., infrastructure vs. user data), each capturing a unique aspect of the problem.

By fusing their outputs, we aim to:

- Leverage complementary information
- Improve prediction accuracy and robustness
- Mitigate individual model biases

Common Fusion Techniques:

- **Simple Average**: Mean of predictions from both models.
- **Weighted Average**: Assigns more importance to the stronger model.
- **Max/Min Fusion**: Takes the most optimistic or conservative prediction.

- **Stacking (Meta-model Fusion)**: Trains a new model on the predictions of sub-models.
- **And there are other methods aswell.**

Our Approach: Stacking (Meta-model Fusion)

We use the predictions from `model_infra` and `model_user` as inputs to a **meta-regressor** (e.g., `LinearRegression`) trained on a **validation set**. This meta-model learns how to best combine the sub-model predictions to improve overall latency prediction accuracy.

Stacking (Meta-model Fusion): Train a meta-regressor on the outputs of both models.

In [11]:
```
# Train meta-model on validation predictions
meta_model = LinearRegression()
meta_model.fit(X_stack_train, y_stack_train)

# Generate test predictions from base models
infra_test_preds = model_infra.predict(X_infra_test)
user_test_preds = model_user.predict(X_user_test)
X_stack_test = np.column_stack((infra_test_preds, user_test_preds))

# Predict using meta-model (stacking fusion)
fused_preds = meta_model.predict(X_stack_test)
```

Evaluate Stacked Fusion

In [12]:
```
mae = mean_absolute_error(y_test, fused_preds)

''' error because in your environment (Python 3.12 with an older version of scikit-learn),
the mean_squared_error function doesn't support the squared argument.'''
#rmse = mean_squared_error(y_test, fused_preds, squared=False)

mse = mean_squared_error(y_test, fused_preds)
rmse = np.sqrt(mse)

r2 = r2_score(y_test, fused_preds)
```

In [13]:
```
# Print scores with formatting
print("Fused Model Evaluation Metrics (Stacked Fusion)\n" + "-"*50)
print(f"Mean Absolute Error (MAE):     {mae:.4f} ms")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f} ms")
print(f"R² Score:                       {r2:.4f}")
```

```
Fused Model Evaluation Metrics (Stacked Fusion)
--------------------------------------------------
Mean Absolute Error (MAE):     21.2235 ms
Root Mean Squared Error (RMSE): 24.9642 ms
R² Score:                       -0.0169
```

> Baseline monolithic model (no partitioning)

In [14]:
```
X_full = data_cleaned.drop(columns=[target])
X_full_train, X_full_test, y_train_full, y_test_full = train_test_split(
    X_full, y, test_size=0.2, random_state=42
)
```

In [15]:
```
baseline_pipeline = Pipeline([
    ('encoder', encoder),
    ('scaler', StandardScaler(with_mean=False)),
    ('regressor', RandomForestRegressor(n_estimators=100, random_state=42))
])
```

In [16]:
```
baseline_pipeline.fit(X_full_train, y_train_full)
baseline_preds = baseline_pipeline.predict(X_full_test)
```

In [17]:
```
baseline_mae = mean_absolute_error(y_test_full, baseline_preds)

#baseline_rmse = mean_squared_error(y_test_full, baseline_preds, squared=False)

mse = mean_squared_error(y_test_full, baseline_preds)
baseline_rmse = np.sqrt(mse)

baseline_r2 = r2_score(y_test_full, baseline_preds)
```

In [18]:
```
# Print scores with formatting
print("Baseline Monolithic Model Evaluation Metrics \n" + "-"*50)
print(f"Mean Absolute Error (MAE):     {baseline_mae:.4f} ms")
print(f"Root Mean Squared Error (RMSE): {baseline_rmse:.4f} ms")
print(f"R² Score:                       {baseline_r2:.4f}")
```

```
Baseline Monolithic Model Evaluation Metrics
--------------------------------------------------
Mean Absolute Error (MAE):     23.1640 ms
Root Mean Squared Error (RMSE): 27.3914 ms
R² Score:                       -0.2242
```

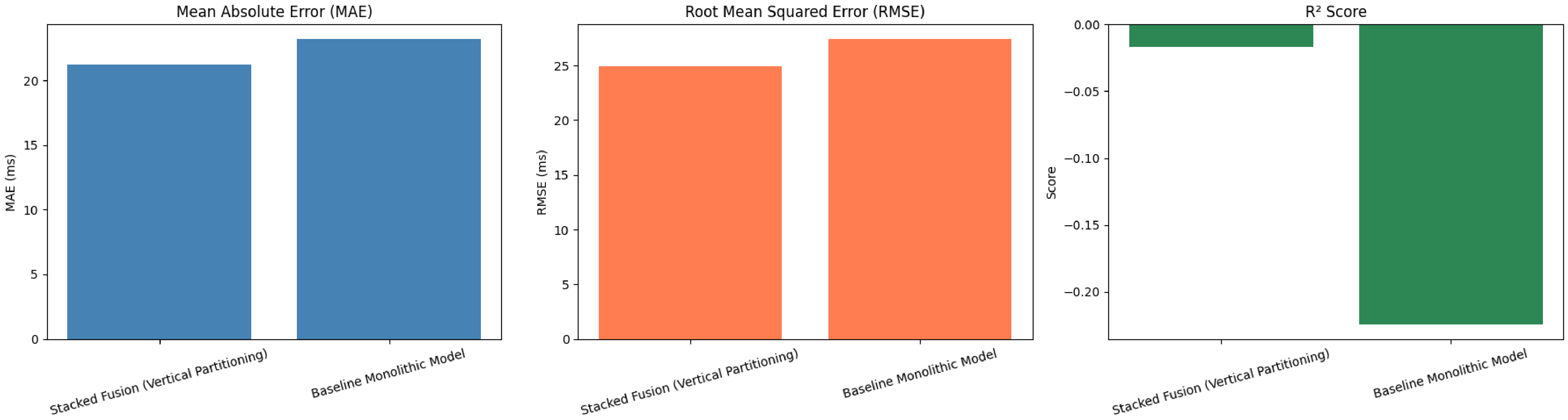
Vertical Partitioning: Model Performance Comparison

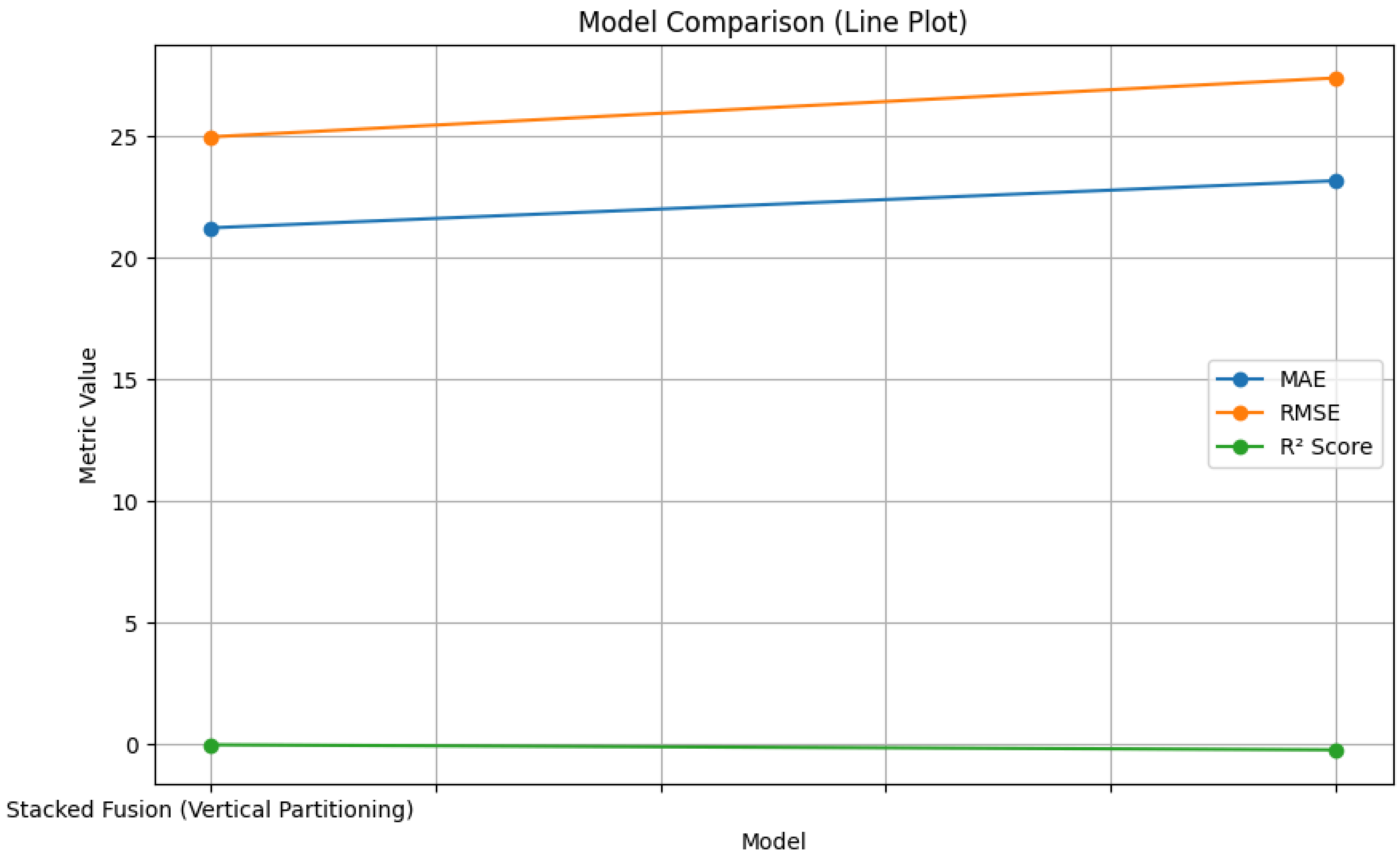
In [19]:
```
performance_table = pd.DataFrame({
    'Model': ['Stacked Fusion (Vertical Partitioning)', 'Baseline Monolithic Model'],
    'MAE': [mae, baseline_mae],
    'RMSE': [rmse, baseline_rmse],
    'R² Score': [r2, baseline_r2]
})

print("Model Performance Comparison:")
print(performance_table)

# Display table
print("Model Performance Comparison:")
display(performance_table)

# 1. Bar Charts
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

axes[0].bar(performance_table['Model'], performance_table['MAE'], color='steelblue')
axes[0].set_title('Mean Absolute Error (MAE)')
axes[0].set_ylabel('MAE (ms)')
axes[0].tick_params(axis='x', rotation=15)

axes[1].bar(performance_table['Model'], performance_table['RMSE'], color='coral')
axes[1].set_title('Root Mean Squared Error (RMSE)')
```

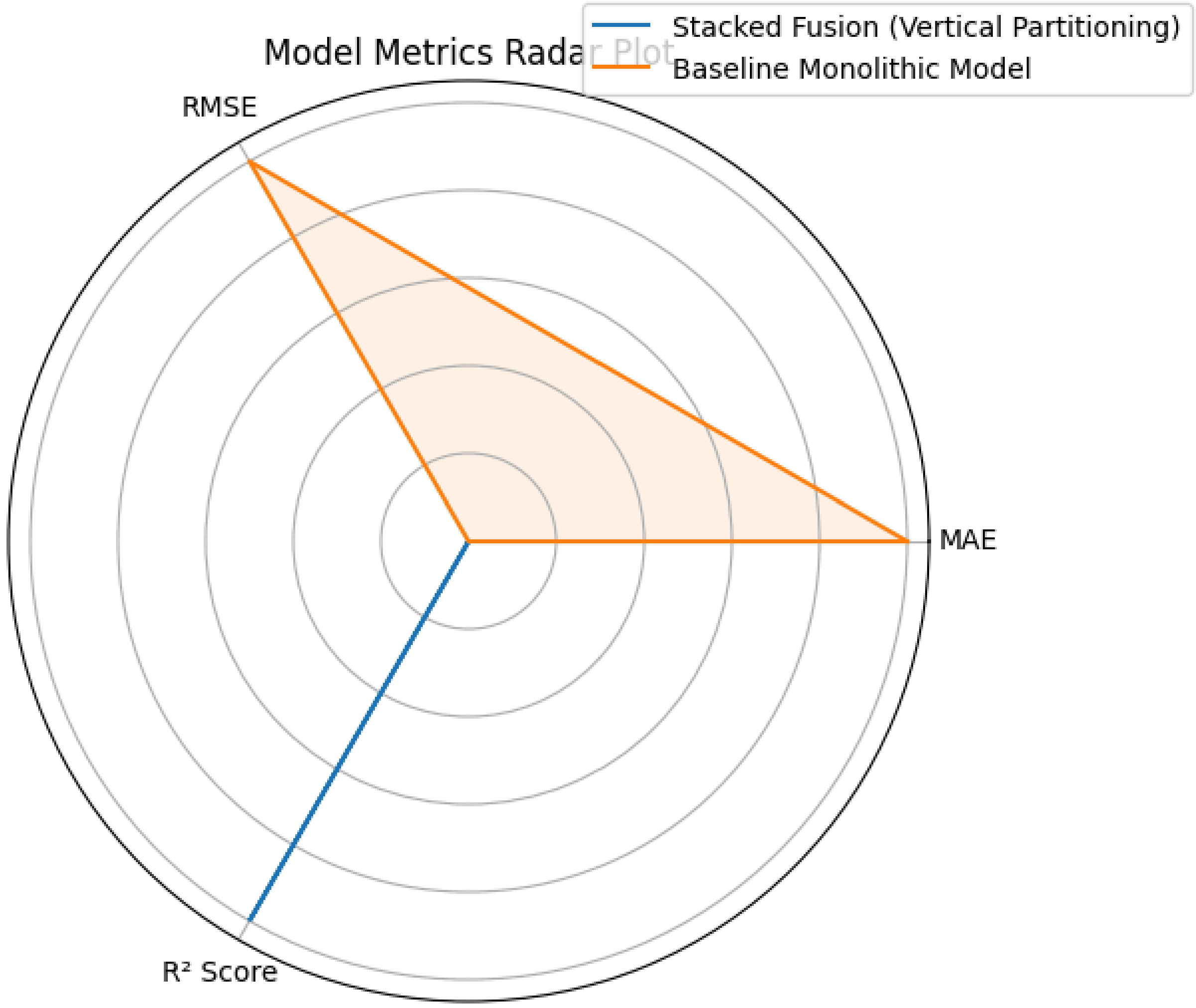
```
axes[1].set_ylabel('RMSE (ms)')
axes[1].tick_params(axis='x', rotation=15)

axes[2].bar(performance_table['Model'], performance_table['R² Score'], color='seagreen')
axes[2].set_title('R² Score')
axes[2].set_ylabel('Score')
axes[2].tick_params(axis='x', rotation=15)

plt.tight_layout()
plt.show()

# 2. Line Plot
performance_table.set_index('Model')[['MAE', 'RMSE', 'R² Score']].plot(
    kind='line', marker='o', figsize=(10, 6), title='Model Comparison (Line Plot)'
)
plt.ylabel('Metric Value')
plt.grid(True)
plt.show()

# 3. Radar Plot
from sklearn.preprocessing import MinMaxScaler
import numpy as np

scaler = MinMaxScaler()
normalized_data = scaler.fit_transform(performance_table[['MAE', 'RMSE', 'R² Score']])
labels = ['MAE', 'RMSE', 'R² Score']
angles = np.linspace(0, 2 * np.pi, len(labels), endpoint=False).tolist()
angles += angles[:1]

fig, ax = plt.subplots(figsize=(6, 6), subplot_kw=dict(polar=True))
for idx, row in enumerate(normalized_data):
    values = row.tolist() + [row[0]]
    ax.plot(angles, values, label=performance_table['Model'][idx])
    ax.fill(angles, values, alpha=0.1)

ax.set_xticks(angles[:-1])
ax.set_xticklabels(labels)
ax.set_yticklabels([])
ax.set_title("Model Metrics Radar Plot")
ax.legend(loc='upper right', bbox_to_anchor=(1.3, 1.1))

plt.show()
```

```
Model Performance Comparison:
                                 Model        MAE       RMSE  R² Score
0  Stacked Fusion (Vertical Partitioning)  21.223541  24.964209 -0.016863
1              Baseline Monolithic Model  23.164000  27.391381 -0.224207
Model Performance Comparison:
```

	Model	MAE	RMSE	R² Score
0	Stacked Fusion (Vertical Partitioning)	21.223541	24.964209	-0.016863
1	Baseline Monolithic Model	23.164000	27.391381	-0.224207


Mean Absolute Error (MAE)
MAE (ms)
Root Mean Squared Error (RMSE)
RMSE (ms)
R² Score
Score
Stacked Fusion (Vertical Partitioning)
Baseline Monolithic Model


Model Comparison (Line Plot)
Metric Value
MAE
RMSE
R² Score
Stacked Fusion (Vertical Partitioning)
Model



Metric	Stacked Fusion (Vertical Partitioning)	Baseline Monolithic Model
MAE	21.22 ms	23.16 ms
RMSE	24.96 ms	27.39 ms
R^2 Score	-0.0169	-0.2242

What's we did

- **Train/val/test split** to avoid data leakage during stacking
- **Meta-model** (`LinearRegression`) learns how to best combine sub-model predictions
- **Performance** is now measured using the fused model output: `fused_preds`

Key Insights

Model Performance

Mean Absolute Error (MAE)

- The **stacked fusion model** has a **lower MAE** than the baseline.
- This means it makes **smaller errors on average** in predicting latency.

Root Mean Squared Error (RMSE)

- Again, the **stacked fusion model** has a **lower RMSE**, indicating that **larger errors are less frequent** compared to the baseline.
- RMSE penalizes large errors more than MAE, so this is a **strong sign** that fusion improves stability.

R^2 Score (Coefficient of Determination)

- Both models have **negative R^2 scores**, which means they perform **worse than a naive mean predictor**.
- However, the **stacked model** has a **less negative R^2**, indicating it's **closer to being useful**.

Overall Conclusion

- **Stacked Fusion (Vertical Partitioning)** clearly **outperforms** the **baseline monolithic model** on both **MAE** and **RMSE**.
- However, **R^2 < 0** signals that **both models need improvement**, possibly due to:
  - Noisy data or insufficient features
  - Non-linear interactions not captured well by the models
  - Need for better feature engineering or deeper models

Improvements that we can do:

- Try more powerful meta-models (e.g., `XGBoostRegressor`, `SVR`) for stacking.

- Explore **polynomial features** or **feature interactions**.

- Check for **data quality issues** or **outliers**.

- Evaluate and engineer **domain-specific features** that might improve latency prediction.

B. Horizontal Partitioning

In this section, we explore horizontal partitioning by categorizing the dataset into two geographical groups: **Urban** and **Rural** cell towers.

We will:

- Manually tag the dataset into urban and rural subsets.
- Train separate models on each subset.
- Train a global model on the full dataset.
- Compare their performances to assess the benefit of horizontal partitioning.

Simulate Urban vs. Rural Groups

In [20]:
```
# Simulate Urban vs Rural Tags
# Assume we don't have explicit location data, so we'll tag towers manually.
data = pd.read_excel('partitioning_dataset.xlsx')
```

```
# Simulate urban/rural by alternating tower IDs (just for demo purposes)
data['Tower Type'] = np.where(data['Tower ID'].str[-1].astype(int) % 2 == 0, 'Urban', 'Rural')

# Confirm distribution
print(data['Tower Type'].value_counts())
```

```
Tower Type
Rural    75
Urban    75
Name: count, dtype: int64
```

Preprocess Data per Subset

In [21]:
```
# Preprocessing
features = ['Signal Strength (dBm)', 'Network Traffic (MB)', 'User Count', 'Device Type']
target = 'Latency (ms)'

encoder = ColumnTransformer(
    transformers=[('cat', OneHotEncoder(), ['Device Type'])],
    remainder='passthrough',
    force_int_remainder_cols=False
)

scaler = StandardScaler(with_mean=False)

pipeline = Pipeline([
    ('encoder', encoder),
    ('scaler', scaler),
    ('regressor', RandomForestRegressor(n_estimators=100, random_state=42))
])
```

Split into Urban and Rural

In [22]:
```
urban_data = data[data['Tower Type'] == 'Urban']
rural_data = data[data['Tower Type'] == 'Rural']
```

Train Models on Urban, Rural, and Full Data

Split and train for Urban

In [23]:
```
X_urban = urban_data[features]
y_urban = urban_data[target]
X_urban_train, X_urban_test, y_urban_train, y_urban_test = train_test_split(X_urban, y_urban, test_size=0.2, random_state=42)
model_urban = pipeline.fit(X_urban_train, y_urban_train)
urban_preds = model_urban.predict(X_urban_test)
```

Split and train for Rural

In [24]:
```
X_rural = rural_data[features]
y_rural = rural_data[target]
X_rural_train, X_rural_test, y_rural_train, y_rural_test = train_test_split(X_rural, y_rural, test_size=0.2, random_state=42)
model_rural = pipeline.fit(X_rural_train, y_rural_train)
rural_preds = model_rural.predict(X_rural_test)
```

Global Model (no partitioning)

In [25]:
```
X_full = data[features]
y_full = data[target]
X_full_train, X_full_test, y_full_train, y_full_test = train_test_split(X_full, y_full, test_size=0.2, random_state=42)
model_full = pipeline.fit(X_full_train, y_full_train)
global_preds = model_full.predict(X_full_test)
```

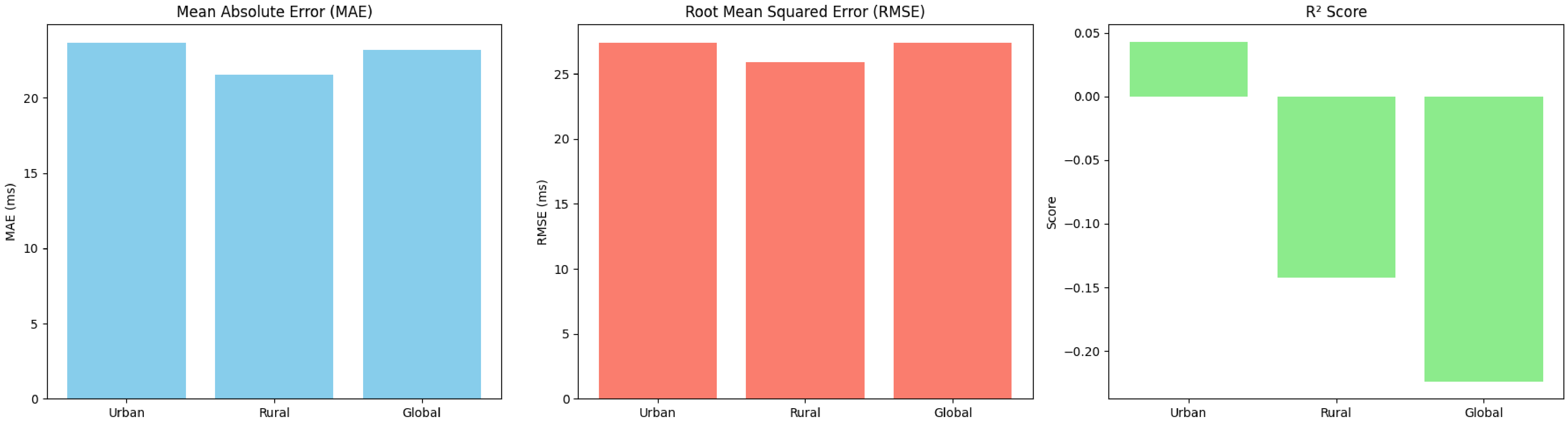
Evaluate & Compare

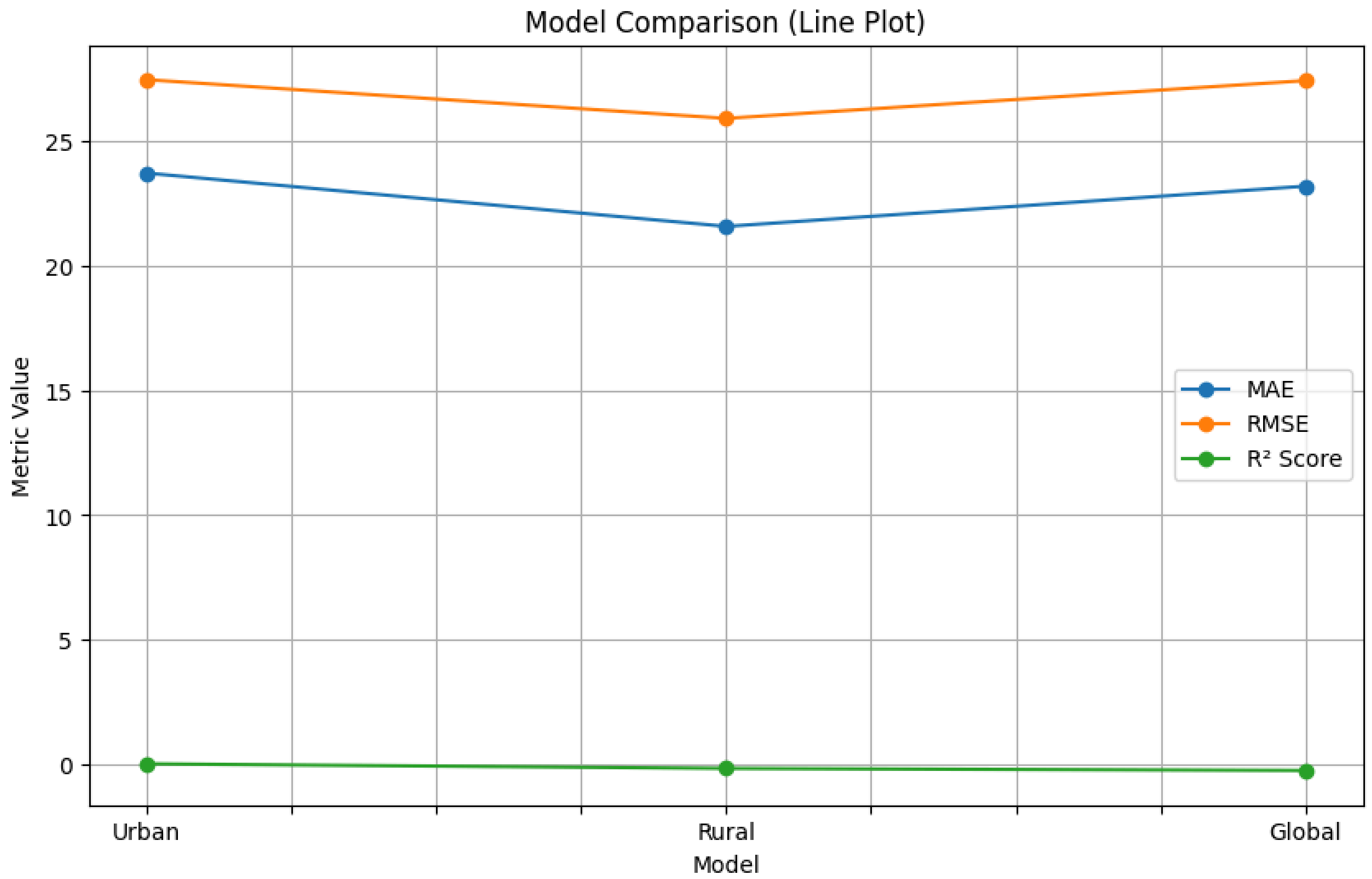
In [26]:
```
# Evaluation function
def evaluate(y_true, y_pred, label):
    mae = mean_absolute_error(y_true, y_pred)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))
    r2 = r2_score(y_true, y_pred)
    print(f"{label} Model Metrics")
    print("-"*40)
    print(f"MAE:  {mae:.4f} ms")
    print(f"RMSE: {rmse:.4f} ms")
    print(f"R²:   {r2:.4f}\n")
    return [label, mae, rmse, r2]

# Collect results
results = []
results.append(evaluate(y_urban_test, urban_preds, 'Urban'))
results.append(evaluate(y_rural_test, rural_preds, 'Rural'))
results.append(evaluate(y_full_test, global_preds, 'Global'))

# Create summary DataFrame
performance_df = pd.DataFrame(results, columns=['Model', 'MAE', 'RMSE', 'R² Score'])
display(performance_df)

# -------------------- Graphs --------------------

# 1. Bar Charts
fig, axes = plt.subplots(1, 3, figsize=(18, 5))

axes[0].bar(performance_df['Model'], performance_df['MAE'], color='skyblue')
axes[0].set_title('Mean Absolute Error (MAE)')
axes[0].set_ylabel('MAE (ms)')

axes[1].bar(performance_df['Model'], performance_df['RMSE'], color='salmon')
axes[1].set_title('Root Mean Squared Error (RMSE)')
axes[1].set_ylabel('RMSE (ms)')

axes[2].bar(performance_df['Model'], performance_df['R² Score'], color='lightgreen')
axes[2].set_title('R² Score')
axes[2].set_ylabel('Score')

plt.tight_layout()
```

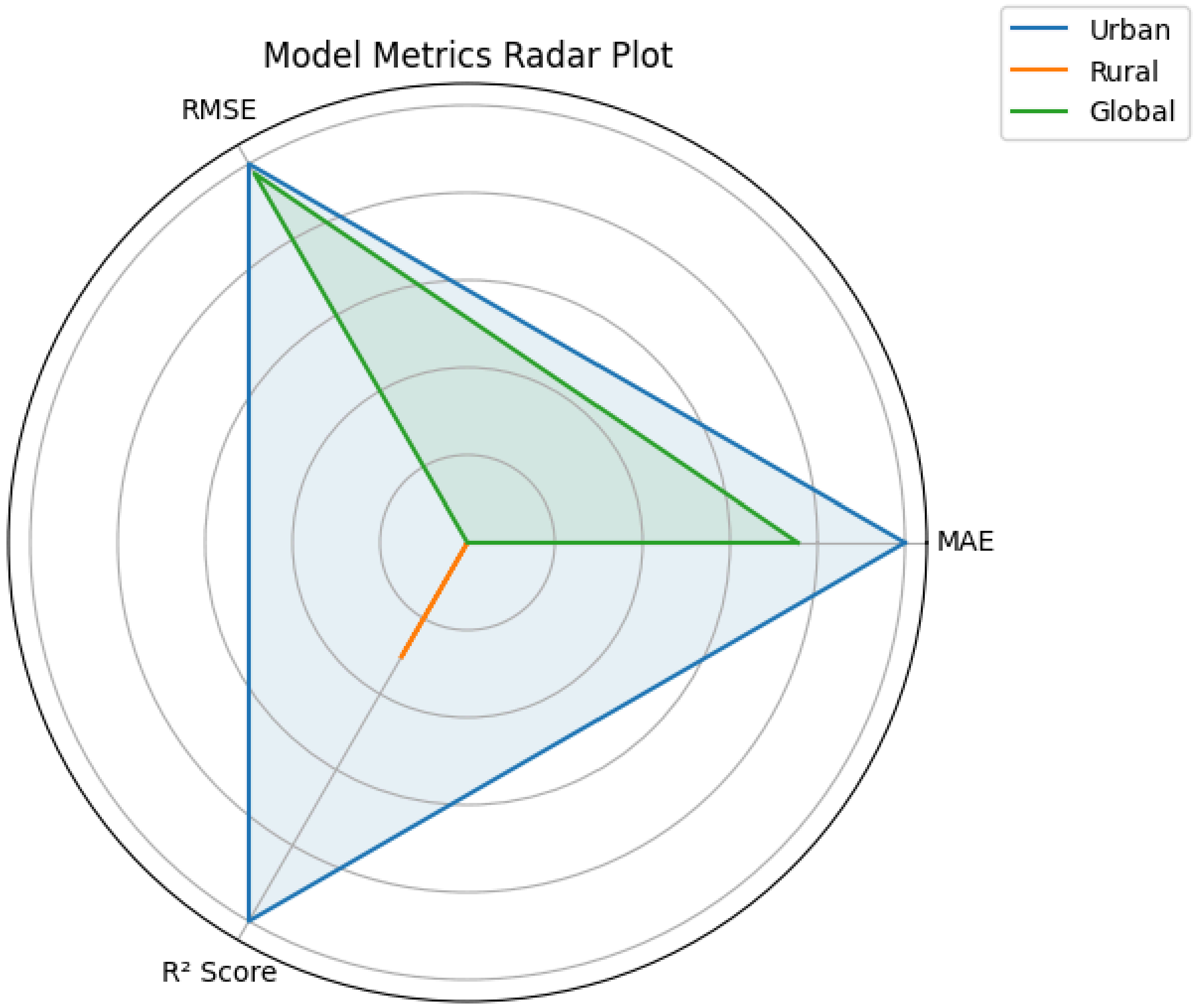
```
plt.show()

# 2. Line Plot
performance_df.set_index('Model')[['MAE', 'RMSE', 'R² Score']].plot(
    kind='line', marker='o', figsize=(10, 6), title='Model Comparison (Line Plot)'
)
plt.ylabel('Metric Value')
plt.grid(True)
plt.show()

# 3. Radar Plot
scaler = MinMaxScaler()
normalized_data = scaler.fit_transform(performance_df[['MAE', 'RMSE', 'R² Score']])
labels = ['MAE', 'RMSE', 'R² Score']
angles = np.linspace(0, 2 * np.pi, len(labels), endpoint=False).tolist()
angles += angles[:1]  # close the loop

fig, ax = plt.subplots(figsize=(6, 6), subplot_kw=dict(polar=True))
for idx, row in enumerate(normalized_data):
    values = row.tolist() + [row[0]]  # complete the loop
    ax.plot(angles, values, label=performance_df['Model'][idx])
    ax.fill(angles, values, alpha=0.1)

ax.set_xticks(angles[:-1])
ax.set_xticklabels(labels)
ax.set_yticklabels([])
ax.set_title("Model Metrics Radar Plot")
ax.legend(loc='upper right', bbox_to_anchor=(1.3, 1.1))

plt.show()
```

```
Urban Model Metrics
----------------------------------------
MAE:  23.6873 ms
RMSE: 27.4300 ms
R²:   0.0432

Rural Model Metrics
----------------------------------------
MAE:  21.5520 ms
RMSE: 25.8793 ms
R²:   -0.1426

Global Model Metrics
----------------------------------------
MAE:  23.1640 ms
RMSE: 27.3914 ms
R²:   -0.2242
```

	Model	MAE	RMSE	R^2 Score
0	Urban	23.687333	27.429967	0.043199
1	Rural	21.552000	25.879302	-0.142586
2	Global	23.164000	27.391381	-0.224207


Mean Absolute Error (MAE)
MAE (ms)
0
5
10
15
20
Urban
Rural
Global
Root Mean Squared Error (RMSE)
RMSE (ms)
0
5
10
15
20
25
Urban
Rural
Global
R² Score
Score
0.05
0.00
−0.05
−0.10
−0.15
−0.20
Urban
Rural
Global


Model Comparison (Line Plot)
Metric Value
0
5
10
15
20
25
Urban
Rural
Global
Model
MAE
RMSE
R² Score



Horizontal Partitioning: Model Performance Comparison

Model	MAE (ms)	RMSE (ms)	R^2 Score
Urban	23.69	27.43	0.0432
Rural	21.55	25.88	-0.1426
Global	23.16	27.39	-0.2242

Key Insights

Urban Model

- **MAE** and **RMSE** are slightly higher than the global model.
- However, **R^2 = 0.0432**, which is **the only positive score** — indicating slight learning beyond the mean.
- ➤ Urban model is modestly better at capturing structure in its own subset.

Rural Model

- **Lowest MAE (21.55 ms)** and **lowest RMSE (25.88 ms)** among all models.
- Still has **negative R^2**, indicating it underperforms a constant mean predictor — but **less poorly than the global model**.

- ➤ Rural model benefits more from specialized learning.

Global Model

- Performs worse than Rural and Urban on both **R^2** and **RMSE**.
- Indicates the model struggles to generalize across all geographic variations.

Conclusion: Is Horizontal Partitioning Beneficial?

- **Horizontal Partitioning** provides benefits, especially when the data distributions of subgroups (e.g., Urban vs Rural towers) differ.
- The **Rural model** outperforms the global model in all metrics — suggesting that local modeling is more effective in less variable or more isolated environments.
- The **Urban model**, while slightly worse on MAE/RMSE, **achieves a positive R^2**, indicating it captures patterns better in complex areas than the global model.

Recommendation:

- For **distributed wireless networks**, deploying **localized models per region or tower type** (Urban/Rural) may improve accuracy and efficiency.
- Use **horizontal partitioning** when:
  - Data is **naturally grouped** (e.g., by tower, region, device type).
  - Each group has **unique patterns** not well represented in a global model.

In [ ]: