In [1]:
```
import pandas as pd # for data manipulation and analysis
import numpy as np
import requests
import seaborn as sns # for data visualization
import matplotlib.pyplot as plt
import plotly.express as px


from sklearn.model_selection import train_test_split # for machine learning
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
# Always show DataFrame as plain text in Jupyter
pd.set_option("display.notebook_repr_html", False)
```

In [2]:
```
# Option 2: Force column 2 to string
df = pd.read_csv("MTA_Subway_Hourly_Ridership__Beginning_2025_20250923.csv", n
```

In [3]:
```
df
```

Out[3]:

```
              transit_timestamp transit_mode station_complex_id  \
0        01/07/2025 06:00:00 PM       subway                339   
1        01/07/2025 06:00:00 PM       subway                340   
2        01/07/2025 06:00:00 PM       subway                340   
3        01/07/2025 06:00:00 PM       subway                340   
4        01/07/2025 06:00:00 PM       subway                343   
...                         ...          ...                ...   
6999995  03/23/2025 12:00:00 PM       subway                636   
6999996  03/23/2025 12:00:00 PM       subway                 64   
6999997  03/23/2025 12:00:00 PM       subway                 64   
6999998  03/23/2025 12:00:00 PM       subway                 65   
6999999  03/23/2025 12:00:00 PM       subway                 65   

                   station_complex   borough payment_method  \
0                  Bergen St (2,3)  Brooklyn      metrocard   
1           Grand Army Plaza (2,3)  Brooklyn      metrocard   
2           Grand Army Plaza (2,3)  Brooklyn      metrocard   
3           Grand Army Plaza (2,3)  Brooklyn      metrocard   
4                 Nostrand Av (3)  Brooklyn      metrocard   
...                            ...       ...            ...   
6999995  Jay St-MetroTech (A,C,F,R)  Brooklyn      metrocard   
6999996                 71 St (D)  Brooklyn      metrocard   
6999997                 71 St (D)  Brooklyn           omny   
6999998                 79 St (D)  Brooklyn      metrocard   
6999999                 79 St (D)  Brooklyn           omny   

                      fare_class_category  ridership  transfers   latitude  \
0             Metrocard - Unlimited 7-Day         12          0  40.680830   
1                   Metrocard - Fair Fare         13          2  40.675236   
2         Metrocard - Seniors & Disability         23          3  40.675236   
3            Metrocard - Unlimited 30-Day         38          0  40.675236   
4                   Metrocard - Full Fare         10          0  40.669846   
...                                   ...        ...        ...        ...   
6999995      Metrocard - Unlimited 30-Day         33          0  40.692337   
6999996       Metrocard - Unlimited 7-Day         12          0  40.619590   
6999997                  OMNY - Students         27          0  40.619590   
6999998      Metrocard - Unlimited 30-Day         14          0  40.613503   
6999999                  OMNY - Students         27          0  40.613503   

         longitude                 Georeference  
0        -73.97510    POINT (-73.9751 40.68083)  
1        -73.97105  POINT (-73.97105 40.675236)  
2        -73.97105  POINT (-73.97105 40.675236)  
3        -73.97105  POINT (-73.97105 40.675236)  
4        -73.95046  POINT (-73.95046 40.669846)  
...            ...                          ...  
6999995  -73.98594  POINT (-73.98594 40.692337)  
6999996  -73.99886   POINT (-73.99886 40.61959)  
6999997  -73.99886   POINT (-73.99886 40.61959)  
6999998  -74.00061  POINT (-74.00061 40.613503)  
6999999  -74.00061  POINT (-74.00061 40.613503)  

[7000000 rows x 12 columns]
```

In [4]:

```python
df['transit_timestamp'] = pd.to_datetime(df['transit_timestamp'])
```

```
C:\Users\Bagdo\AppData\Local\Temp\ipykernel_1420\3131658029.py:1: UserWarning:
Could not infer format, so each element will be parsed individually, falling b
ack to `dateutil`. To ensure parsing is consistent and as-expected, please spe
cify a format.
  df['transit_timestamp'] = pd.to_datetime(df['transit_timestamp'])
```

In [5]:
```
df.shape
```

Out[5]:
```
(7000000, 12)
```

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
transit_timestamp      0
transit_mode           0
station_complex_id     0
station_complex        0
borough                0
payment_method         0
fare_class_category    0
ridership              0
transfers              0
latitude               0
longitude              0
Georeference           0
dtype: int64
```

In [7]:
```
df['station_complex'] = df['station_complex'].str.replace(r'\(.*\)', '', regex=
```

In [8]:
```
df['month'] = df['transit_timestamp'].dt.month
df['day'] = df['transit_timestamp'].dt.day
df['hour'] = df['transit_timestamp'].dt.hour
df['ridership'] = df['ridership']
df['day_of_week'] = df['transit_timestamp'].dt.dayofweek  # 0=Mon, 6=Sun
df['is_weekend'] = df['day_of_week'].isin([5,6]).astype(int)
```

In [9]:
```
df = df.groupby(['month', 'day', 'hour','borough','is_weekend','day_of_week'])
```

In [10]:
```
df = pd.get_dummies(df, columns=['borough'], prefix='borough')
```

In [ ]:

In [11]:
```
X = df[['month', 'day', 'hour','borough_Queens','borough_Manhattan','borough_S
       'is_weekend']]
y = df['ridership']

# Split the data into 80% training and 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, randon
```

In [12]:
```
# Split the data into features and labels
labels = np.array(df['ridership'])
features = df.drop('ridership', axis=1)
feature_list = list(features.columns)
features = np.array(features)
```

In [13]:
```
df["borough_Queens"] = df["borough_Queens"].astype(int)
df["borough_Manhattan"] = df["borough_Manhattan"].astype(int)
df["borough_Staten Island"] = df["borough_Staten Island"].astype(int)
```

```python
df["borough_Bronx"] = df["borough_Bronx"].astype(int)
df["borough_Brooklyn"] = df["borough_Brooklyn"].astype(int)

df["is_weekend"] = df["is_weekend"].astype(int)
```

In [14]:
```python
features
```

Out[14]:
```
array([[1, 4, 0, ..., False, False, False],
       [1, 4, 0, ..., False, False, False],
       [1, 4, 0, ..., True, False, False],
       ...,
       [7, 25, 21, ..., True, False, False],
       [7, 25, 22, ..., True, False, False],
       [7, 25, 23, ..., True, False, False]], dtype=object)
```

In [15]:
```python
train_features, test_features, train_labels, test_labels = train_test_split(
    features, labels, test_size=0.25, random_state=38
)
```

In [ ]:
```python

```

In [ ]:
```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV

# Define the model
rf = RandomForestRegressor(random_state=38)

# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 400],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2']
}

# Set up GridSearchCV
grid_search = GridSearchCV(
    estimator=rf,
    param_grid=param_grid,
    cv=3,                   # 3-fold cross validation
    n_jobs=-1,              # use all CPU cores
    verbose=2,
    scoring='r2'            # optimize for R²
)

# Fit grid search to training data
grid_search.fit(train_features, train_labels)


# Best hyperparameters
print("✅ Best Parameters:", grid_search.best_params_)
print("✅ Best R² Score:", grid_search.best_score_)
```

In [21]:
```python
rf_best = RandomForestRegressor(
    max_depth=20,
    max_features='sqrt',
    min_samples_leaf=1,
    min_samples_split=2,
```

```python
    n_estimators=400,
    random_state=38
)

rf_best.fit(train_features, train_labels)
```

Out[21]:

```
RandomForestRegressor

RandomForestRegressor(max_depth=20, max_features='sqrt', n_estimators=
400,
                      random_state=38)
```

In [22]:

```python
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
import numpy as np

predictions = rf_best.predict(test_features)

mae = mean_absolute_error(test_labels, predictions)
r2 = r2_score(test_labels, predictions)
rmse = np.sqrt(mean_squared_error(test_labels, predictions))
smape = 100 * np.mean(
    2 * np.abs(predictions - test_labels) / (np.abs(test_labels) + np.abs(predi
)

print("MAE:", round(mae, 2))
print("RMSE:", round(rmse, 2))
print("R²:", round(r2, 3))
print("SMAPE:", round(smape, 2), "%")
```

```
MAE: 2903.57
RMSE: 7940.28
R²: 0.963
SMAPE: 33.63 %
```

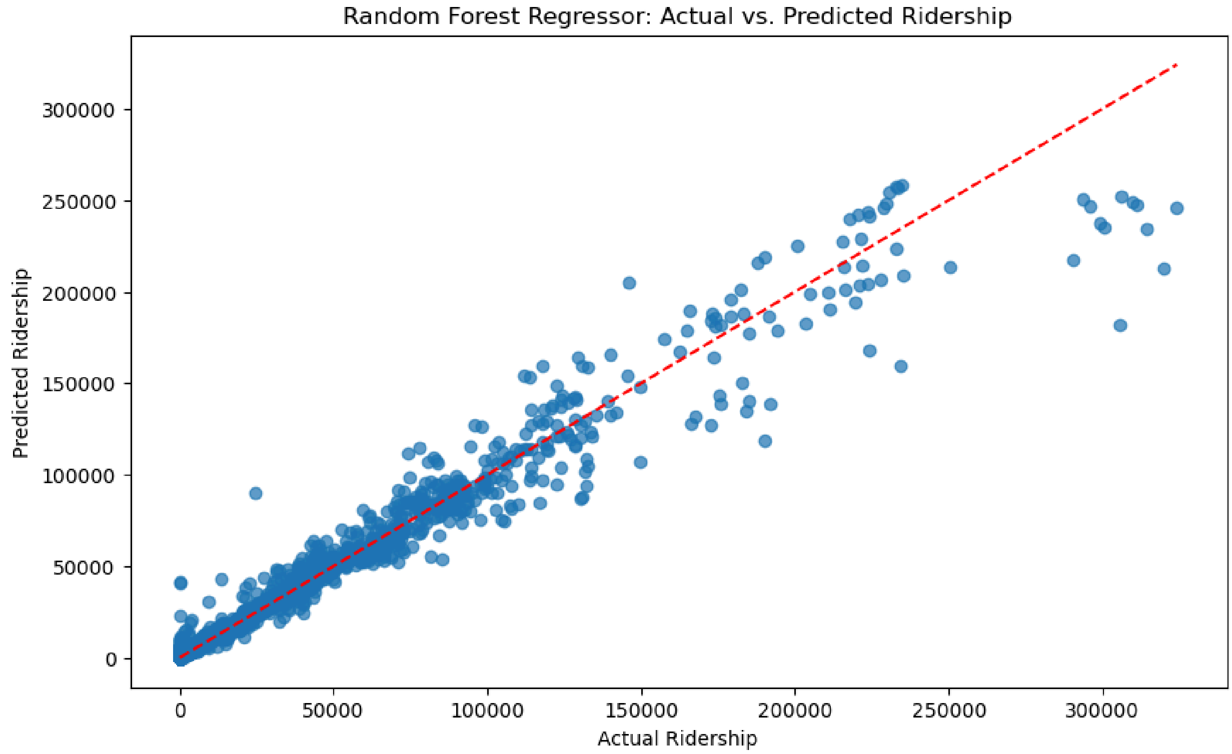
In [57]:

```python
import joblib

# Save the model
joblib.dump(rf_best, "rf_best_model.pkl")

print("Model saved successfully.")
```

```
Model saved successfully.
```

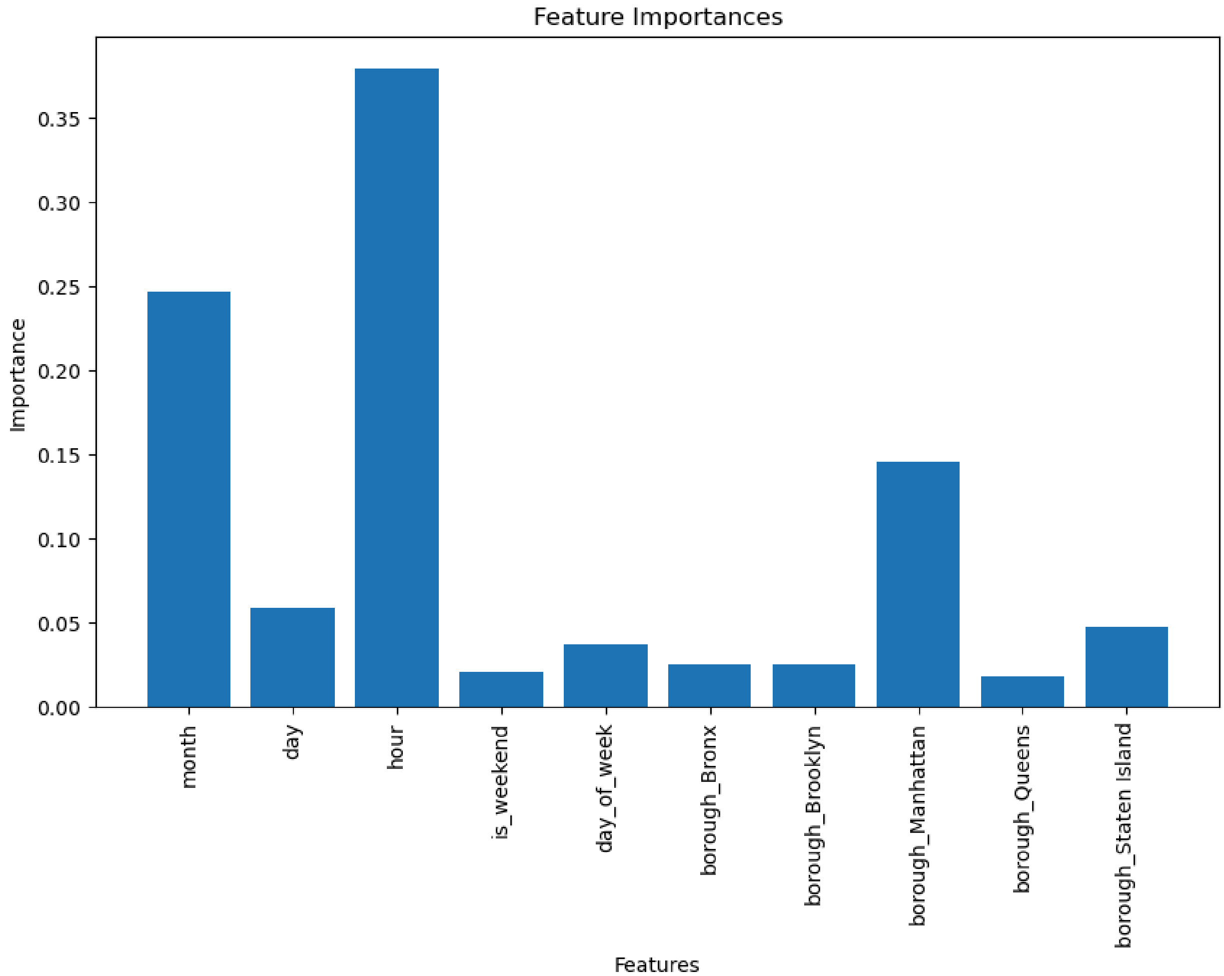
In [23]:

```python
plt.figure(figsize=(10, 6))
plt.scatter(test_labels, predictions, alpha=0.7)
plt.plot([min(test_labels), max(test_labels)], [min(test_labels), max(test_labe

plt.xlabel('Actual Ridership')
plt.ylabel('Predicted Ridership')
plt.title('Random Forest Regressor: Actual vs. Predicted Ridership')
plt.show()
```



In [24]:
```
# Train the model on training data
rf_best.fit(train_features, train_labels)

# Get feature importances
feature_importances = rf_best.feature_importances_

# Associate feature importances with feature names
feature_importance_list = list(zip(feature_list, feature_importances))

# Print the top N most important features and their importances
for feature, importance in feature_importance_list:
    print(f"{feature}: {importance}")

# Create a bar plot to visualize feature importances
plt.figure(figsize=(10, 6))
plt.bar(range(len(feature_importances)), feature_importances)
plt.xticks(range(len(feature_importances)), [feature[0] for feature in feature_
plt.xlabel('Features')
plt.ylabel('Importance')
plt.title('Feature Importances')
plt.show()
```

```
month: 0.24629933840117232
day: 0.058390589192784656
hour: 0.3794652151485105
is_weekend: 0.02004113932981861
day_of_week: 0.036758673830466354
borough_Bronx: 0.024615045293072985
borough_Brooklyn: 0.024401961573944538
borough_Manhattan: 0.14534189969349828
borough_Queens: 0.017730882875768083
borough_Staten Island: 0.0469552546609638
```


Feature Importances
Importance
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
month
day
hour
is_weekend
day_of_week
borough_Bronx
borough_Brooklyn
borough_Manhattan
borough_Queens
borough_Staten Island
Features

In [39]:
```
df
```

Out[39]:

```
       month  day  hour  is_weekend  day_of_week  ridership  borough_Bronx  \
0          1    4     0           1            5       1163              1
1          1    4     0           1            5       5272              0
2          1    4     0           1            5      24702              0
3          1    4     0           1            5       2823              0
4          1    4     0           1            5         63              0
...      ...  ...   ...         ...          ...        ...            ...
12639      7   25    19           0            4        509              0
12640      7   25    20           0            4        500              0
12641      7   25    21           0            4        421              0
12642      7   25    22           0            4        299              0
12643      7   25    23           0            4        149              0

       borough_Brooklyn  borough_Manhattan  borough_Queens  \
0                     0                  0               0
1                     1                  0               0
2                     0                  1               0
3                     0                  0               1
4                     0                  0               0
...                 ...                ...             ...
12639                 0                  1               0
12640                 0                  1               0
12641                 0                  1               0
12642                 0                  1               0
12643                 0                  1               0

       borough_Staten Island
0                          0
1                          0
2                          0
3                          0
4                          1
...                      ...
12639                      0
12640                      0
12641                      0
12642                      0
12643                      0

[12644 rows x 11 columns]
```

In [40]:

```python
def predict_and_show_ridership(month, day, hour, borough, day_of_week=None, is_
    # Borough list in same order as columns
    boroughs = ['Bronx', 'Brooklyn', 'Manhattan', 'Queens', 'Staten Island']
    borough_encoding = [1 if b == borough else 0 for b in boroughs]

    # Calculate day_of_week if not provided
    if day_of_week is None:
        try:
            date = pd.Timestamp(year=2025, month=month, day=day)
            day_of_week = date.dayofweek
        except Exception as e:
            print("Invalid date:", e)
            return

    # Calculate is_weekend if not provided
    if is_weekend is None:
        is_weekend = int(day_of_week in [5, 6])

    # Build input in exact column order
```

```python
    input_data = [[month, day, hour, is_weekend, day_of_week] + borough_encodi

    # Predict
    predicted_ridership = rf_best.predict(input_data)

    # Find actual ridership if exists
    actual_ridership = df[
        (df['month'] == month) &
        (df['day'] == day) &
        (df['hour'] == hour) &
        (df[f'borough_{borough}'] == 1)
    ]['ridership']

    actual_ridership = actual_ridership.values[0] if len(actual_ridership) > 0

    print(f"Input: Month={month}, Day={day}, Hour={hour}, Borough={borough}, Da
    print(f"Predicted Ridership: {round(predicted_ridership[0], 2)}")
    print(f"Actual Ridership: {actual_ridership}")
```

In [56]:
```python
predict_and_show_ridership(month=2, day=2, hour=1, borough="Brooklyn", day_of_
```

```
Input: Month=2, Day=2, Hour=1, Borough=Brooklyn, Day_of_week=2, Is_weekend=0
Predicted Ridership: 1594.06
Actual Ridership: 3596
```

In [ ]:

In [ ]: