

AIR TRAFFIC FLOW MANAGEMENT OPTIMIZATION

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INTRODUCTION:

Air traffic flow management (ATFM) optimization is a critical area in aviation aiming to streamline air traffic movement for efficiency, safety, and cost reduction. Imagine a complex network of airplanes vying for space in the sky. ATFM steps in to ensure this network runs smoothly, especially when demand surpasses available airspace or airport capacity.

OBJECTIVES :

ATFM optimization aims to strategically manage traffic flow to reduce ground delays and airborne holding patterns

This involves strategies like optimized routing to avoid bottlenecks and scheduling arrivals and departures to prevent congestion.

Improved efficiency translates to smoother traffic flow and potentially even increased capacity in the long run.

Optimization strategies consider factors like weather patterns and separation requirements to prevent situations that could lead to mid-air incidents.

predictable flight times and minimized delays, airlines can optimize crew scheduling, fuel planning, and ground handling, leading to overall cost reduction.

system requirements:

The data contained in this dataset has been US Automatic Traffic Recorder Stations Data (kaggle.com)

This comprehensive dataset records important information about Automatic Traffic Recorder (ATR) Stations located across the United States.

The dataset comprises a collection of attributes for each station such as its location details (latitude, longitude), AADT or The Annual Average Daily Traffic amount, classification of road where it's located etc...

Sttnkey: A unique identifier for each station.

NHS: Indicates if the station is part of national highway system.

Location: Describes specific location of a station with street or highway name.

Comment: Any additional remarks related to that station.

Longitude, Latitude: Geographic coordinates.

STPostal: The postal code where a given station resides.

ADT: Annual Average Daily Traffic count indicating average volume of vehicles passing through that route annually divided by 365 days

Year_GEO: The year when geographic information was last updated - can provide insight into recency or timeliness of recorded attribute values

METHODOLOGY:

1. Demand and Capacity Analysis:

Demand Forecasting: Historical data, weather predictions, and airline schedules are analyzed to predict the volume and type of air traffic in a specific airspace or airport.

Capacity Assessment: The available airspace and airport infrastructure are evaluated to determine the maximum number of aircraft they can safely handle. This considers factors like weather limitations, runway configurations, and staffing levels.

2. Strategic Planning:

Flow Management Programs: Based on the demand-capacity analysis, centralized Air Traffic Control (ATC) authorities develop flow management programs (FMPs). These programs might include:

Ground Delay Programs (GDPs): Strategically delaying departures to regulate the number of aircraft entering the airspace.

Ground Stops: Temporarily halting departures from specific airports due to severe congestion or airspace limitations.

Rerouting Strategies: Optimizing flight paths to avoid congested areas or utilize available airspace more efficiently.

3. Real-time Traffic Management:

Tactical Decision Making: Air Traffic Controllers (ATCs) use real-time data on weather, aircraft positions, and potential conflicts to make adjustments to the planned flow. This might involve:

Sequencing Arrivals and Departures: Prioritizing aircraft for landing and takeoff to maintain a safe and efficient flow.

Speed Adjustments: Directing aircraft to adjust their speed to maintain separation and avoid delays.

Holding Patterns: Instructing aircraft to enter holding patterns when necessary to manage traffic flow.

4. Technological Advancements:

Machine Learning and Data Analytics: These technologies are increasingly used to analyze vast datasets and predict traffic patterns with greater accuracy. This allows for more proactive and data-driven optimization strategies.

Advanced Communication Systems: Real-time communication between airlines, ATCs, and other stakeholders is crucial for effective flow management. Advanced data sharing platforms and communication protocols facilitate smoother coordination.

5. Collaboration and Information Sharing:

Airline Cooperation: Airlines play a vital role by providing accurate flight plans and being flexible with scheduling adjustments when requested by ATFM authorities.

International Coordination: For international flights, close collaboration between different air traffic control agencies is essential for seamless flow management across borders.

model EVALUATION

REGERSSION METRICS:

R-squared (R^2): This metric represents the proportion of variance in the target variable (AADT) that can be explained by the linear regression model. It ranges from 0 (no explanatory power) to 1 (perfect fit). A higher R^2 indicates a better fit.

Mean Squared Error (MSE): This metric calculates the average squared difference between the predicted values (y_{pred}) and the actual values (y_{test}). Lower MSE signifies a better fit.

Mean Absolute Error (MAE): This metric calculates the average absolute difference between the predicted values and the actual values. MAE is less sensitive to outliers compared to MSE. Lower MAE indicates a better fit.

Median Absolute Error (Median AE): This metric represents the middle value of the absolute errors between predicted and actual values. It's less affected by extreme values compared to MAE. Lower Median AE indicates a better fit.

Ranking Metrics:

Spearman Rank Correlation Coefficient: This metric measures the monotonic relationship between the predicted and actual values, regardless of the magnitude of the differences. It ranges from -1 (perfect negative correlation) to 1 (perfect positive correlation). A value closer to 1 indicates a strong positive ranking relationship.

Kendall Tau Rank Correlation Coefficient: Similar to Spearman's rank correlation, this metric measures the similarity between the ordering of the predicted and actual values. It ranges from -1 (perfect negative correlation) to 1 (perfect positive correlation). A value closer to 1 indicates a strong agreement in ranking between predicted and actual values.

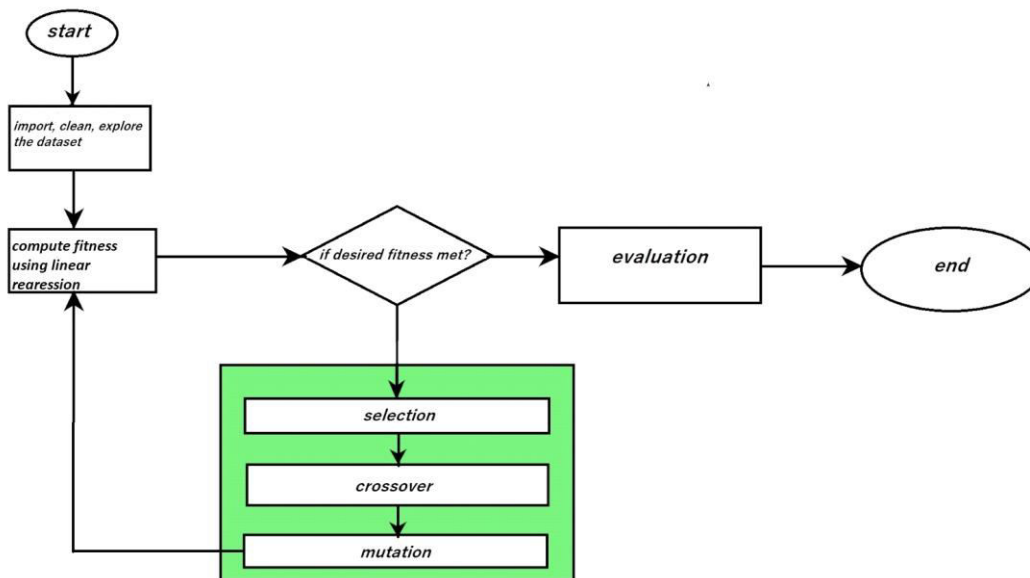
existing work:

A wealth of research exists in ATFM optimization, with advancements in machine learning for traffic prediction, collaborative decision-making tools, dynamic airspace concepts, and optimization algorithms aiming to improve efficiency, while exploring integration with automation for a future of smoother traffic flow and reduced human error.

proposed work :

Proposed work in ATFM aims to leverage cutting-edge technologies like AI and real-time data analysis to develop even more precise traffic forecasting models. This would allow for proactive flow management strategies like dynamic airspace allocation and collaborative decision-making platforms, ultimately leading to smoother traffic flow, reduced delays and emissions, and a more resilient air transport system in the face of emerging challenges like drone integration.

FLOW CHART:



code:

```
import pandas as pd
import seaborn as sns
data =pd.read_csv('Automatic_Traffic_Recorder_ATR_Stations (1) (1).csv')
```

#The data description are given....

```
print(data.head())
print(data.tail())
print(data.info())
print(data.describe())
```

the null data handling are given....

```
print(data.isnull().sum())
m = data.dropna()
print(m)
```

#the data validation are given...

```
print (data['VERSION'].unique())
```

#the data reshaping are given....

```
transposed_data=data.T
print(transposed_data)
```

```
# the data aggregation are given...
grouped_data = data.groupby('VERSION')
aggregated_data = grouped_data.agg('VERSION')
print(aggregated_data)
print(grouped_data)
```

#the data vidualization are given...

```
import matplotlib.pyplot as plt
class univariate:
    def hist(self):
        columns = ['LONGITUDE', 'LATITUDE', 'AADT','CTFIPS']
        fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(12, 8))
        for i, col in enumerate(columns[:10]):
            num_subplots = len(columns)
            rows, cols = divmod (num_subplots, 2)
            for i, col in enumerate(columns):
                row, col_index = divmod(i, 2)
                axes[row, col_index].hist(data[col], bins='auto')
                axes[row, col_index].set_xlabel(col)
                axes[row, col_index].set_ylabel('CustomerID',)
                axes[row, col_index].set_title(col)
        fig.suptitle("Histogram")
        plt.tight_layout()
        plt.show()
```

```
def bar(self):
    columns = ['LONGITUDE', 'LATITUDE', 'AADT','CTFIPS']
    plt.figure(figsize=(12, 6))
    for i, col_name in enumerate(columns ):
        x_axis = data['LONGITUDE']
        y_axis = data[col_name]
        plt.subplot(1, len(columns), i + 1)
        plt.bar(x_axis, y_axis, label=col_name)
        plt.xlabel(data.columns[0])
        plt.ylabel(col_name)
    plt.suptitle('Bar Chart ')
```

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

```
a=univariate()
univariate.hist(a)
univariate.bar(a)
print(f"the end of univariate visualization ")
```

```
class bivariate:
    def scatter(self):
        columns = ['LONGITUDE', 'LATITUDE', 'AADT','CTFIPS']
        rows = int((len(columns) - 1) / 2) + 1
        cols = min(2, len(columns))
        fig, axes = plt.subplots(rows, cols, figsize=(12, 8))
        col_index = 0
        for i in range(rows):
            for j in range(cols):
                if col_index >= len(columns):
                    break;
                ax = axes[i, j]
                x = data['LONGITUDE']
                y = data[columns[col_index]]
                fig.suptitle("Scatter plot",weight='bold')
                ax.scatter(x, y, color='blue', marker='o', edgecolors='black', alpha=0.7)
                ax.set_xlabel('LONGITUDE')
                ax.set_ylabel(columns[col_index] )
                ax.set_title('LONGITUDE vs ' + columns[col_index])
                col_index += 1

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

```
b=bivariate()
bivariate.scatter(b)
```

```

print(f"the end of bivariate visualization")
class multivariate:
    def pairplot(self):
        columns = ['LONGITUDE', 'LATITUDE', 'AADT','CTFIPS']
        sns.pairplot(data=data[columns],height=1.5,palette="husl",diag_kind="hist")
        plt.figure(figsize=(12, 6))
        plt.subplots_adjust(left=0.1, bottom=0.1, right=0.9, top=0.9, wspace=1.5, hspace=1.4)
        plt.tight_layout()
        plt.show()
c=multivariate()
multivariate.pairplot(c)
print(f'the end of multivariate')
import plotly.express as px
class interactive:
    def hist(self):

        fig = px.histogram(x=data['LONGITUDE'],y=data['LATTITUDE'],title='Interactive
Histogram').update_layout(xaxis_title='LONGITUDE',yaxis_title='LATTITUDE')
        fig.show()

    def scatter(self):
        fig = px.scatter(x=data['LONGITUDE'],y=data['LATTITUDE'],title='Interactive Scatter
plot ')
        fig.show()

d=interactive()
interactive.hist(d)
interactive.scatter(d)
print(f'the end of interactive visualization')

```

```

from sklearn.linear_model import LinearRegression

```



```
from sklearn.model_selection import train_test_split, GridSearchCV

from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error,
median_absolute_error

from scipy.stats import spearmanr, kendalltau

from sklearn.preprocessing import StandardScaler # Import StandardScaler


# Load your data into a pandas DataFrame

data = pd.read_csv("Automatic_Traffic_Recorder_ATR_Stations (1).csv") # Replace with
your data file path


# Select features and target variable

X = data[["LONGITUDE", "LATITUDE"]]

y = data["AADT"]


# Split data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# *Data Normalization (Alternative to hyperparameter tuning):*

# Create a StandardScaler object

scaler = StandardScaler()


# Fit the scaler on the training data (learn mean and standard deviation)

scaler.fit(X_train)


# Normalize both training and testing data using the fitted scaler

X_train_scaled = scaler.transform(X_train)

X_test_scaled = scaler.transform(X_test)
```

```
# Define hyperparameter grid for LinearRegression (without 'normalize')

hyperparameter_grid = {

    'fit_intercept': [True, False] # Whether to fit an intercept term

}


# Create and train the linear regression model with hyperparameter tuning

model = GridSearchCV(LinearRegression(), hyperparameter_grid, cv=5, scoring='r2')

model.fit(X_train_scaled, y_train)


# Get the best model with tuned hyperparameters

best_model = model.best_estimator_


# Make predictions on testing data using the best model

y_pred = best_model.predict(X_test_scaled)


# ... (rest of your code for evaluation metrics)


# Evaluate the model using various metrics

r2 = r2_score(y_test, y_pred)

print("R-squared (Proportion of variance explained):", r2)


mse = mean_squared_error(y_test, y_pred)

print("Mean Squared Error (Average squared difference):", mse)


mae = mean_absolute_error(y_test, y_pred)

print("Mean Absolute Error (Average absolute difference):", mae)
```

```
median_ae = median_absolute_error(y_test, y_pred)
```

```
print("Median Absolute Error:", median_ae)
```

```
# Ranking Metrics
```

```
spearman_rho, _ = spearmanr(y_test, y_pred) # Spearman's rank correlation coefficient
```

```
print("Spearman Rank Correlation Coefficient:", spearman_rho)
```

```
kendall_tau, _ = kendalltau(y_test, y_pred) # Kendall's rank correlation coefficient
```

```
print("Kendall Tau Rank Correlation Coefficient:", kendall_tau)
```

```
# Print the best hyperparameter configuration
```

```
print("Best Hyperparameters:", model.best_params_)
```

```
print('end of the code')
```

OUT PUT:

```

FID 6006
STTNKEY 02000002
STTNID 000002
NHS 0
LOCATION RAIG/KLAHOCK/HOLLIS HWY BTW KLAHOCK R. BR. & BAYV
CONFIDENCE 3
COMMENT Not on NHPN
LONGITUDE -133.088078
LATITUDE 55.550582
STPOSTAL AK
AADT 2028
YEAR_GEO 2001
FCLASS 7
STFIPS 2
CTFIPS 0
VERSION 1

6 \
Index 6
X -132.36462
Y 56.467185
FID 6007
STTNKEY 02000003
STTNID 000003
NHS 0
LOCATION RANGELL PTR: ZIMOVIA HWY BTW BENNET & CASE WRAN
CONFIDENCE 3
COMMENT
LONGITUDE -132.36462
LATITUDE 56.467186
STPOSTAL AK
AADT 2113
YEAR_GEO 2001
FCLASS 7
STFIPS 2
CTFIPS 280
VERSION 1

7 \
Index 7
X -132.951902
Y 56.776219
FID 6008
```

FID 6004
STTNKEY 02000800
STTNID 000800
NHS 0
LOCATION AMDEN PTR BTW DOCK & PARK KETCHIKAN
CONFIDENCE 2
COMMENT Not on NHPN
LONGITUDE -131.640004
LATITUDE 55.344761
STPOSTAL AK
AADT 0
YEAR_GEO 2001
FCLASS
STFIPS 2
CTFIPS 0
VERSION 1

4 \
Index 4
X -131.711563
Y 55.377654
FID 6005
STTNKEY 02000801
STTNID 000801
NHS 0
LOCATION TONGASS BTW S & N JCTS W/SORELINE DR, KETCHIKAN
CONFIDENCE 3
COMMENT
LONGITUDE -131.711563
LATITUDE 55.377654
STPOSTAL AK
AADT 0
YEAR_GEO 2001
FCLASS
STFIPS 2
CTFIPS 130
VERSION 1

5 \
Index 5
X -133.088078
Y 55.558582
FID 6006
STTNKEY 02000802

LOCATION EST END BADGER LOOP ROAD (NB)
CONFIDENCE 2
COMMENT Poor Location Description
LONGITUDE -147.565704
LATITUDE 64.818031
STPOSTAL AK
AADT 10620
YEAR_GEO 2001
FCLASS 17
STFIPS 2
CTFIPS 90
VERSION 1

2 \
Index 2
X -147.803037
Y 64.849282
FID 6003
STTNKEY 02000532
STTNID 000532
NHS 7
LOCATION OHANSEN EXPRESSWAY EAST OF UNIVERSITY AVENUE (EB)
CONFIDENCE 2
COMMENT
LONGITUDE -147.803037
LATITUDE 64.849282
STPOSTAL AK
AADT 20866
YEAR_GEO 2001
FCLASS 14
STFIPS 2
CTFIPS 90
VERSION 1

3 \
Index 3
X -131.640005
Y 55.344761
FID 6004
STTNKEY 02000800
STTNID 000800
NHS 0
LOCATION AMDEN PTR BTW DOCK & PARK KETCHIKAN

```
1 2001 17 2 90 1
2 2001 14 2 90 1
3 2001 2 0 1
4 2001 2 130 1
...
6344 1999 6 95 1
6345 2000 6 95 1
6346 1999 6 95 1
6347 1999 6 95 1
6348 2000 12 6 97 1
```

[6349 rows x 19 columns]
[1]

```
0 \
Index 0
X -147.799672
Y 64.837219
FID 6001
STTNKEY 02000530
STTNID 000530
NHS 3
LOCATION IRPORT WAY BETWEEN MARKET STREET AND UNIVERSITY A
CONFIDENCE 3
COMMENT
LONGITUDE -147.799672
LATITUDE 64.837219
STPOSTAL AK
AADT 15330
YEAR_GEO 2001
FCLASS 14
STFIPS 2
CTFIPS 90
VERSION 1
```

```
1 \
index 1
X -147.565705
Y 64.818031
FID 6002
STTNKEY 02000531
STTNID 000531
NHS 0
LOCATION EST END BADGER LOOP ROAD (NB)
```

```
otype: int64
index X Y FID STTNKEY STTNID NHS \
0 0 -147.799672 64.837219 6001 02000530 000530 3
1 1 -147.565705 64.818031 6002 02000531 000531 0
2 2 -147.803037 64.849282 6003 02000532 000532 7
3 3 -131.640005 55.344761 6004 02000800 000800 0
4 4 -131.711563 55.377654 6005 02000801 000801 0
...
6344 6344 -122.086734 38.242014 996 06043334 043334 1
6345 6345 -122.101213 38.235599 997 06043340 043340 1
6346 6346 -122.101298 38.235561 998 0604334E 04334E 1
6347 6347 -122.101256 38.235580 999 0604334W 04334W 1
6348 6348 -122.714518 38.431792 1000 06044040 044040 3
```

```
LOCATION CONFIDENCE \
0 IRPORT WAY BETWEEN MARKET STREET AND UNIVERSITY A 3
1 EST END BADGER LOOP ROAD (NB) 2
2 OHANSEN EXPRESSWAY EAST OF UNIVERSITY AVENUE (EB) 2
3 AWDEN PTR BTW DOCK & PARK KETCHIKAN 2
4 TONGASS BTW S & N JCTS W/SORELINE DR, KETCHIKAN 3
...
6344 ABERNATHY LANE (WAS 10004W7) 3
6345 .5MILEW/ORTE12EAST 3
6346 .5 MILE W/O RTE 12 EAST 3
6347 .5 MILE W/O RTE 12 EAST 3
6348 JCTRTE12 3
```

```
COMMENT LONGITUDE LATITUDE STPOSTAL AADT \
0 -147.799672 64.837219 AK 15330
1 Poor Location Description -147.565704 64.818031 AK 10620
2 -147.803037 64.849282 AK 20866
3 Not on NHPN -131.640004 55.344761 AK 0
4 -131.711563 55.377654 AK 0
...
6344 -122.086733 38.242014 CA 0
6345 -122.101213 38.235599 CA 0
6346 -122.101298 38.235561 CA 0
6347 -122.101255 38.235580 CA 0
6348 -122.714518 38.431792 CA 105045
```

```
YEAR_GEO FCLASS STFIPS CTFIPS VERSION
0 2001 14 2 90 1
1 2001 17 2 90 1
2 2001 14 2 90 1
```

```
CONFIDENCE  LONGITUDE  LATITUDE  AADT  YEAR_GEO \
count 6349.000000 6349.000000 6349.000000 6349.000000 6349.000000
mean 2.830524 -92.207418 39.439932 12501.190581 1995.132777
std 0.437608 15.816166 5.570506 27710.539367 93.802239
min 0.000000 -159.404750 19.502810 0.000000 0.000000
25% 3.000000 -100.126822 36.092894 0.000000 1999.000000
50% 3.000000 -88.076386 39.759902 83.000000 1999.000000
75% 3.000000 -81.196029 42.992022 12071.000000 2000.000000
max 3.000000 -67.370606 64.979661 322369.000000 2005.000000
```

```
STFIPS  CTFIPS  VERSION
count 6349.000000 6349.000000 6349.0
mean 29.542605 71.852659 1.0
std 15.322071 94.834270 0.0
min 1.000000 0.000000 1.0
25% 19.000000 13.000000 1.0
50% 27.000000 49.000000 1.0
75% 41.000000 103.000000 1.0
max 56.000000 820.000000 1.0
```

```
index
X
Y
FID
STTNKEY
STTNID
NHS
LOCATION
CONFIDENCE
COMMENT
LONGITUDE
LATITUDE
STPOSTAL
AADT
YEAR_GEO
FCLASS
STFIPS
CTFIPS
VERSION
dtype: int64
```

```
index X Y FID STTNKEY STTNID NHS \
0 0 -147.799672 64.837219 6001 02000530 000530 3
1 1 -147.565705 64.818031 6002 02000531 000531 0
```

```
STPOSTAL  AADT  YEAR_GEO  FCLASS  STFIPS  CTFIPS  VERSION
6344 CA 0 1999 6 95 1
6345 CA 0 2000 6 95 1
6346 CA 0 1999 6 95 1
6347 CA 0 1999 6 95 1
6348 CA 105045 2000 12 6 97 1
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6349 entries, 0 to 6348
Data columns (total 19 columns):
```

```
# Column Non-Null Count Dtype
---
0 index 6349 non-null int64
1 X 6349 non-null float64
2 Y 6349 non-null float64
3 FID 6349 non-null int64
4 STTNKEY 6349 non-null object
5 STTNID 6349 non-null object
6 NHS 6349 non-null int64
7 LOCATION 6349 non-null object
8 CONFIDENCE 6349 non-null int64
9 COMMENT 6349 non-null object
10 LONGITUDE 6349 non-null float64
11 LATITUDE 6349 non-null float64
12 STPOSTAL 6349 non-null object
13 AADT 6349 non-null int64
14 YEAR_GEO 6349 non-null int64
15 FCLASS 6349 non-null object
16 STFIPS 6349 non-null int64
17 CTFIPS 6349 non-null int64
18 VERSION 6349 non-null int64
```

```
dtypes: float64(4), int64(9), object(6)
```

```
memory usage: 942.6+ KB
```

```
None
index X Y FID NHS \
count 6349.000000 6349.000000 6349.000000 6349.000000 6349.000000
mean 3174.000000 -92.207418 39.439932 3175.000000 2.425894
std 1832.942761 15.816166 5.570506 1832.942761 2.927780
min 0.000000 -159.404750 19.502810 1.000000 0.000000
25% 1587.000000 -100.126822 36.092894 1588.000000 0.000000
50% 3174.000000 -88.076386 39.759902 3175.000000 1.000000
75% 4761.000000 -81.196029 42.992022 4762.000000 7.000000
max 6348.000000 -67.370607 64.979661 6349.000000 9.000000
```



▲

	6345	6346 \
Index	6345	6346
X	-122.101213	-122.101298
Y	38.235599	38.235561
FID	997	998
STTNKEY	06043340	0604334E
STTNID	043340	04334E
NHS	1	1
LOCATION	.5MILEW/ORTE12EAST	.5 MILE W/O RTE 12 EAST
CONFIDENCE	3	3
COMMENT		
LONGITUDE	-122.101213	-122.101298
LATITUDE	38.235599	38.235561
STPOSTAL	CA	CA
AADT	0	0
YEAR_GEO	2000	1999
FCLASS		
STFIPS	6	6
CTFIPS	95	95
VERSION	1	1

	6347	6348
Index	6347	6348
X	-122.101256	-122.714518
Y	38.23558	38.431792
FID	999	1000
STTNKEY	0604334W	06044040
STTNID	04334W	044040
NHS	1	3
LOCATION	.5 MILE W/O RTE 12 EAST	JCT RTE12
CONFIDENCE	3	3
COMMENT		
LONGITUDE	-122.101255	-122.714518
LATITUDE	38.23558	38.431792
STPOSTAL	CA	CA
AADT	0	105045
YEAR_GEO	1999	2000
FCLASS		12
STFIPS	6	6
CTFIPS	95	97
VERSION	1	1

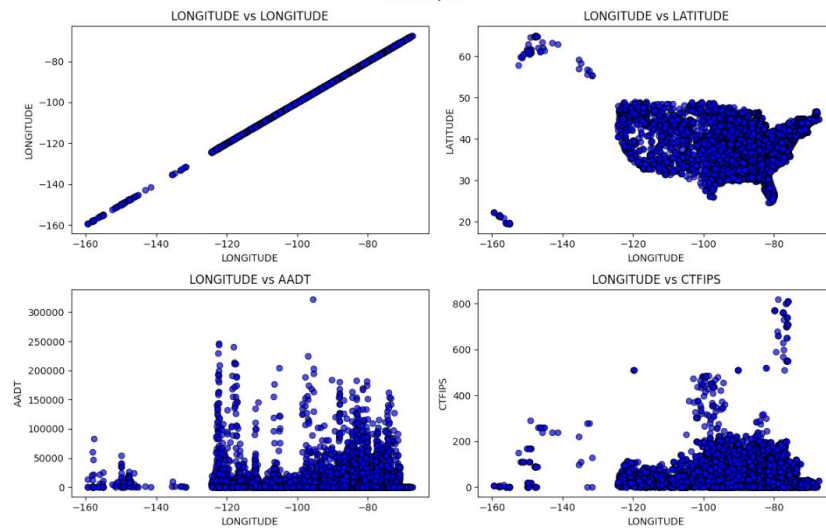
[19 rows x 6349 columns]

	6339	6340	6341 \
Index	6339	6340	6341
X	-124.210640	-124.210640	-122.929746
Y	40.622209	40.622209	39.074249
FID	991	992	993
STTNKEY	0601110N	0601110S	06017720
STTNID	01110N	01110S	017720
NHS	3	3	0
LOCATION	JCT RTE 1, SINGLEY RD IC	JCT RTE 1, SINGLEY RD IC	S/OPARKWAY
CONFIDENCE	2	2	3
COMMENT			
LONGITUDE	-124.210648	-124.210648	-122.929745
LATITUDE	40.622209	40.622209	39.07425
STPOSTAL	CA	CA	CA
AADT	0	0	12614
YEAR_GEO	1999	1999	2000
FCLASS			2
STFIPS	6	6	6
CTFIPS	23	23	33
VERSION	1	1	1

	6342	6343	6344 \
Index	6342	6343	6344
X	-121.045207	-121.328546	-122.086734
Y	38.945374	38.33099	38.242014
FID	994	995	996
STTNKEY	06034580	06035010	06043334
STTNID	034580	035010	043334
NHS	1	7	1
LOCATION	BOWMAN-PLA-80-R23.43	N/OARNORROAD	ABERNATHY LANE (WAS 10004W7)
CONFIDENCE	2	3	3
COMMENT			
LONGITUDE	-121.045207	-121.328545	-122.086733
LATITUDE	38.945374	38.33099	38.242014
STPOSTAL	CA	CA	CA
AADT	39726	67598	0
YEAR_GEO	2000	2000	1999
FCLASS	1	2	
STFIPS	6	6	6
CTFIPS	61	67	95
VERSION	1	1	1

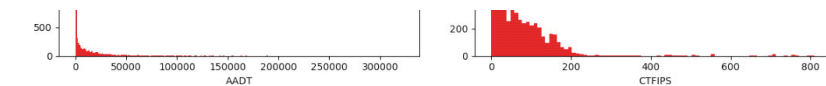
the end of univariate visualization

Scatter plot

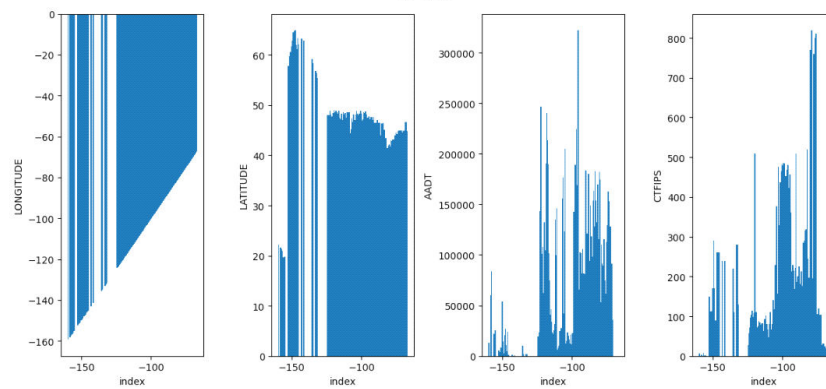


the end of bivariate visualization

/usr/local/lib/python3.10/dist-packages/seaborn/axisgrid.py:1513: UserWarning: Ignoring 'palette' because no 'hue' variable has been assigned.



Bar Chart

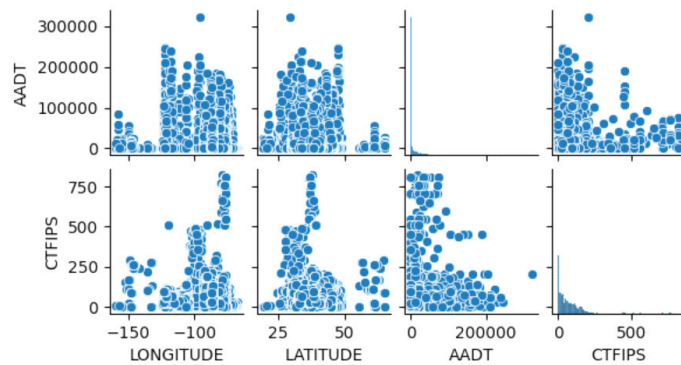
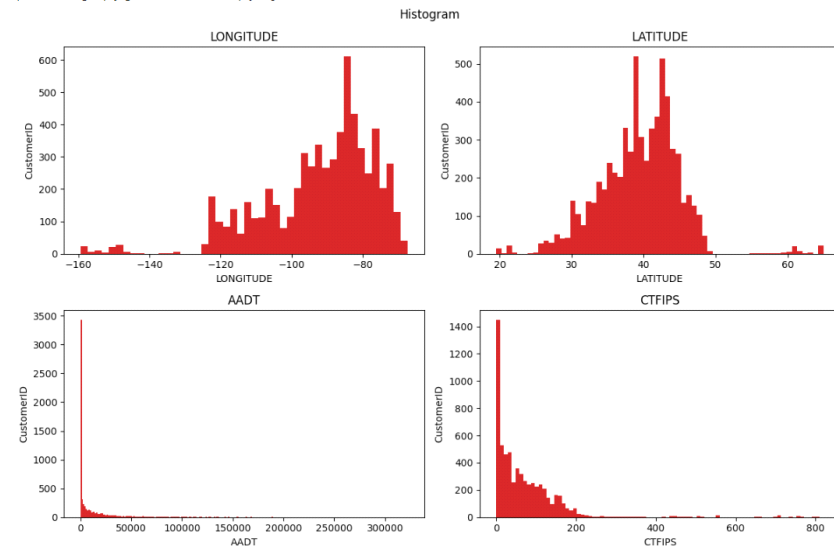


the end of univariate visualization

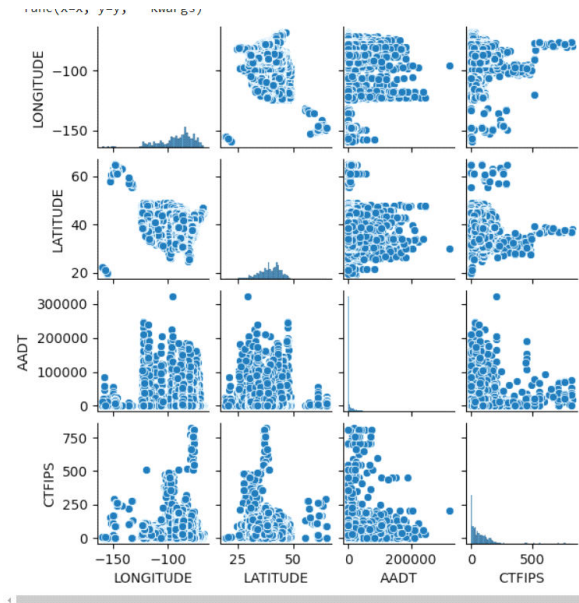
Scatter plot



```
[ 47 ] INFO A. V. 2022-11-28 10:10:10
<pandas.core.groupby.generic.SeriesGroupBy object at 0x7eea39fc5570>
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x7eea39fc4e80>
```



```
<Figure size 1200x600 with 0 Axes>
the end of multivariate
R-squared (Proportion of variance explained): 0.009399250045855623
Mean Squared Error (Average squared difference): 810056787.4575367
Mean Absolute Error (Average absolute difference): 16197.888074329161
Median Absolute Error: 10978.073010069096
Spearman Rank Correlation Coefficient: 0.11492142786729159
Kendall Tau Rank Correlation Coefficient: 0.08192798553360979
Best Hyperparameters: {'fit_intercept': True}
end of the code
```



CONCLUSION:

ATFM optimization plays a critical role in ensuring a safe, efficient, and sustainable air transport system. By strategically managing air traffic flow, it aims to minimize delays, reduce fuel consumption and emissions, and maintain safety within airspace limitations. By embracing these advancements and fostering collaboration, ATFM optimization can continue to play a vital role in shaping a resilient and sustainable air transport system for the future.