

Time series forecasting of the pre-event Air RPM (Revenue Passenger Miles) series using Moving average and Holt Exponential smoothing methods.

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https://github.com/jeeet25/Holt_Exponential_Smoothing-and-Moving-Average

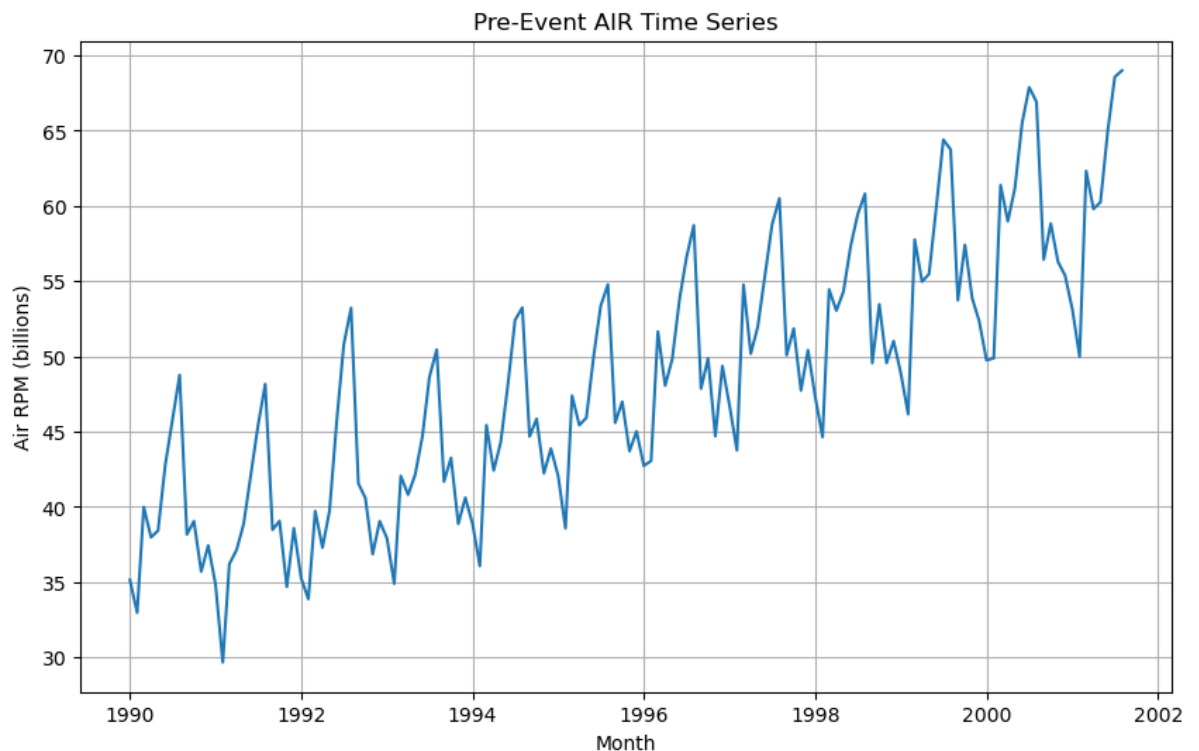
```
In [ ]: import pandas as pd
        from datetime import datetime
        import matplotlib.pyplot as plt

        # Load the data from the CSV file
        data = pd.read_csv('air_miles.csv')
```

```
In [31]: data['Month'] = pd.to_datetime(data['Month'], format='%b-%y')

        pre_event_data = data[data['Month'] < pd.to_datetime('2001-09-01')]
```

```
In [32]: plt.figure(figsize=(10, 6))
        plt.plot(pre_event_data['Month'], pre_event_data['Air RPM (billions)'])
        plt.xlabel('Month')
        plt.ylabel('Air RPM (billions)')
        plt.title('Pre-Event AIR Time Series')
        plt.grid(True)
        plt.show()
```



Since the time plot shows the presence of trend, seasonality, and random fluctuations in the Air RPM series, it becomes evident that the data demonstrates a combination of sustained long-term changes (trend) and repetitive short-term fluctuations (seasonality). we can proceed with analyzing and selecting the most appropriate smoothing method.

Considering the characteristics observed in the plot, Moving average with what window width range of (2-4) OR the Holt Exponential Smoothing method would likely be the most suitable choice for forecasting this time series.

```
In [42]: summary_stats = pre_event_data['Air RPM (billions)'].describe()  
print(summary_stats)
```

```
count      140.000000  
mean        48.213286  
std         8.691648  
min         29.670000  
25%         41.650000  
50%         47.960000  
75%         53.977500  
max         69.000000  
Name: Air RPM (billions), dtype: float64
```

```
In [60]: # Moving Average (with window width)
window_width = 2
pre_event_data['Moving_Average'] = pre_event_data['Air RPM (billion

#Holt Exponential Smoothing (assuming alpha and beta values)
alpha = 0.4
beta = 0.1
pre_event_data['Holt_Exponential_Smoothing'] = pre_event_data['Air

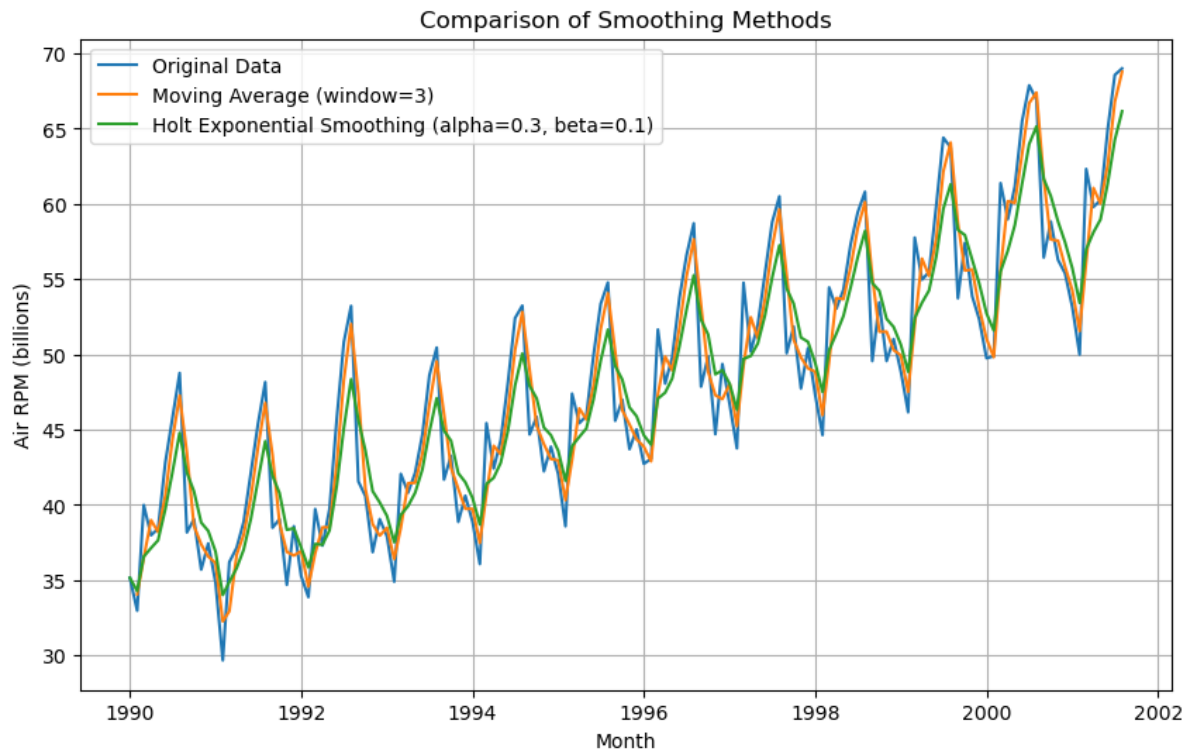
print(pre_event_data)
```

| | Month | Air RPM (billions) | Air RPM | Moving_Average \ |
|-----|------------|--------------------|----------|------------------|
| 0 | 1990-01-01 | 35.15 | 35153577 | NaN |
| 1 | 1990-02-01 | 32.97 | 32965187 | 34.060 |
| 2 | 1990-03-01 | 39.99 | 39993913 | 36.480 |
| 3 | 1990-04-01 | 37.98 | 37981886 | 38.985 |
| 4 | 1990-05-01 | 38.42 | 38419672 | 38.200 |
| ... | ... | ... | ... | ... |
| 135 | 2001-04-01 | 59.80 | 59801562 | 61.060 |
| 136 | 2001-05-01 | 60.25 | 60246477 | 60.025 |
| 137 | 2001-06-01 | 64.99 | 64987625 | 62.620 |
| 138 | 2001-07-01 | 68.57 | 68573410 | 66.780 |
| 139 | 2001-08-01 | 69.00 | 69003617 | 68.785 |

| | Simple_Exponential_Smoothing | Holt_Exponential_Smoothing |
|-----|------------------------------|----------------------------|
| 0 | 35.150000 | 35.150000 |
| 1 | 34.496000 | 34.278000 |
| 2 | 36.144200 | 36.562800 |
| 3 | 36.694940 | 37.129680 |
| 4 | 37.212458 | 37.645808 |
| .. | ... | ... |
| 135 | 57.817170 | 58.111434 |
| 136 | 58.547019 | 58.966860 |
| 137 | 60.479913 | 61.376116 |
| 138 | 62.906939 | 64.253670 |
| 139 | 64.734858 | 66.152202 |

```
[140 rows x 6 columns]
```

```
In [61]: plt.figure(figsize=(10, 6))
plt.plot(pre_event_data['Month'], pre_event_data['Air RPM (billions)'])
plt.plot(pre_event_data['Month'], pre_event_data['Moving_Average']),
plt.plot(pre_event_data['Month'], pre_event_data['Holt_Exponential_
plt.xlabel('Month')
plt.ylabel('Air RPM (billions)')
plt.title('Comparison of Smoothing Methods')
plt.legend()
plt.grid(True)
plt.show()
```



The Moving Average smoothing method with a window width of 2 provides the best fit for forecasting the pre-event Air RPM (billions) series.