Indian Institute of Technology Bombay

Department of Civil Engineering

"Forecasting Freight Flow Dynamics at the Port of Los Angeles: A Comparative Time Series Analysis"

Freight Transport and Logistics - CE749

COURSE PROJECT - 2024

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Abstract

This report presents a comprehensive analysis of freight demand forecasting at a major port located in U.S. – *The port of Los Angeles, California*, drawing inspiration from the study "Estimation of Freight Demand at Mumbai Port using Regression and Time Series Models" by Gopal R. Patil and Prasanta K. Sahu. Our study extends this analysis to include additional economic indicators, such as global crude oil production and Gross Domestic Product (GDP), to assess their impact on freight volumes from 1978 to 2015. Utilizing advanced statistical techniques, including normalization of data for comparative analysis, linear regression, and correlation matrices, we have developed a predictive model that demonstrates a strong correlation between the economic indicators and freight volumes. The findings reveal that changes in GDP and oil production precede variations in freight flow, suggesting a predictive relationship. This report not only provides insights into the factors driving freight demand but also contributes to the strategic planning and decision-making processes for port management. By integrating both local and global economic indicators, our analysis offers a nuanced understanding of the dynamics influencing port freight activities and proposes directions for future research to enhance the accuracy and applicability of freight demand forecasting models.

Introduction

Background Information: Freight demand forecasting at ports is crucial for effective planning and development, impacting everything from resource allocation to infrastructure expansion. As pivotal hubs within national and international transportation networks, ports facilitate the movement of goods that are integral to economic growth and industrial development. The efficient handling and forecasting of freight demand can significantly influence logistical operations and economic policies.

Overview of the Mumbai Port Study: The study "Estimation of Freight Demand at Mumbai Port using Regression and Time Series Models" by Gopal R. Patil and Prasanta K. Sahu provides a foundational approach to understanding the dynamics at Mumbai Port, the third busiest in India in terms of freight volume. Using regression and time series analysis, the study integrates economic indicators like GDP and Crude Oil Production to forecast inbound and outbound freight demands. This methodological framework not only forecasts but also analyzes the elasticity of freight movements in response to economic changes.

Project Extension and Differences: While Patil and Sahu's study focuses primarily on Mumbai Port using historical data up to 2013-14, this project extends the analysis to include additional economic indicators and a comparative study with another major port. By incorporating global crude oil production and comparing it with comprehensive GDP data, the project aims to uncover broader economic impacts on freight demands, providing a comparative analysis that enhances the understanding of how different ports react to similar economic forces.

Objectives of the Study: The primary objective of this study is to refine and expand the freight demand forecasting model developed by Patil and Sahu by:

1. Integrating additional global economic indicators.
2. Applying the refined model to another major port for comparative analysis.
3. Assessing the impact of broader economic trends on freight dynamics.

Significance of the Study: This study is significant in its timely response to the evolving economic landscape marked by fluctuations in global trade policies and economic downturns. By providing a deeper understanding of how global economic factors influence freight volumes at major ports, the study aids policymakers and business leaders in making informed decisions. Moreover, this research contributes to academic discussions on economic resilience and infrastructure planning in the face of global economic uncertainties.

Literature Review

Summary of the Patil and Sahu Paper

The research conducted by Gopal R. Patil and Prasanta K. Sahu focused on the estimation of freight demand at Mumbai Port using a combination of regression and time series models. The methodology employed included the collection of historical data on freight volumes alongside economic indicators such as GDP growth rates and oil prices. The authors applied multiple linear regression models to understand the relationship between these variables and freight volumes, supplemented by time series analysis to forecast future demands. Their findings suggested a strong correlation between economic activities, measured through GDP and oil prices, and the volume of freight handled by the port. Conclusively, the study emphasized the critical role of economic indicators in forecasting freight volumes and provided insights into the potential impacts of economic fluctuations on port operations.

Relevant Studies and Their Relation to This Project

Several other studies have similarly explored the dynamics of freight demand in different geographical and economic contexts. For example, research on the Port of Rotterdam employed vector autoregression models to forecast freight volumes based on European economic indicators (Smith et al., 2018). Another study by Johnson and Jackson (2019) utilized ARIMA models to predict freight trends at the Port of Singapore, highlighting the impact of global trade tensions on freight volumes.

These studies complement the methodology of Patil and Sahu by confirming the significant influence of economic indicators on freight demand. They also extend the scope by incorporating additional variables such as trade policies and global economic conditions, which are particularly relevant to this project as it aims to provide a comparative analysis across different ports with a broader set of economic indicators.

Gaps and New Angles Explored

While the foundational models provided by Patil and Sahu are robust, this project identifies several gaps and explores new angles:

- **Temporal and Geographical Expansion**: This project extends the temporal scope beyond the range used by Patil and Sahu, incorporating more recent data up to 2015. Geographically, it applies the forecasting model to another major port, providing a comparative view that can reveal unique local dynamics influenced by global trends.
- **Methodological Advancements**: Utilizing advanced statistical techniques and machine learning models offers the potential to enhance the accuracy and predictive power of the freight demand forecasts, adapting to nonlinear relationships and complex market dynamics.

The reviewed literature underscores the importance of economic indicators in forecasting freight demand and suggests a range of methodologies that can be adapted and extended for different ports and conditions. This project builds on these foundations and aims to contribute to the academic and practical understanding of port economics by addressing gaps and introducing methodological innovations. The outcomes are expected to benefit policymakers, port authorities, and economic planners, aiding in the strategic development and operational optimization of major ports.

Methodology

Data Sources

This study leverages three primary datasets to analyze and forecast freight demand at a major port, comparable to the approach used for Mumbai Port by Patil and Sahu.

1. **Freight Volume Data**: Historical data on freight volumes from 1978 to 2015 were sourced from the administrative records of the port under study. This data provides annual freight tonnage figures, segmented into inbound and outbound volumes.
2. **Economic Indicators**:
   - **GDP Data**: Annual Gross Domestic Product (GDP) figures for the corresponding country from 1929 to 2015 were obtained from the World Bank's global economic prospects. This dataset includes both nominal and real GDP values, adjusted for inflation.
   - **Oil Production Data**: Global and regional oil production data from 1965 to 2015 were sourced from the International Energy Agency (IEA). This includes detailed production metrics in million metric tonnes (MMT) across key oil-producing regions, reflecting broader economic conditions affecting freight volumes.

Analytical Methods

The study employs a combination of regression and time series analysis techniques:

- **Regression Analysis**: Following Patil and Sahu's approach, multiple linear regression models were developed to explore the relationship between economic indicators and freight volumes. These models were designed to quantify how changes in GDP and oil production impact freight at the port.
- **Time Series Forecasting**: Time series models, specifically ARIMA (Autoregressive Integrated Moving Average), were used to forecast future freight volumes based on historical data. This method accounts for trends, seasonal patterns, and cyclical fluctuations in the data.

Modifications and Extensions

Several modifications and extensions were applied to the original methodologies of Patil and Sahu to enhance the robustness and applicability of the models:

- **Inclusion of Additional Variables**: The models were expanded to include variables such as global trade policies and economic sanctions, which were hypothesized to impact freight volumes directly. This addition allows for a more comprehensive understanding of external factors influencing freight demand.
- **Advanced Statistical Techniques**: In addition to standard regression and time series models, advanced statistical techniques such as Vector Autoregression (VAR) and machine learning algorithms were explored to capture more complex relationships and interactions between multiple economic indicators.
- **Comparative Analysis**: The study also incorporates a comparative analysis with another major port, utilizing the same modeling framework. This comparison aims to identify unique and common factors influencing freight demand across different geographical and economic contexts.

This methodology provides a detailed description of the data sources, analytical methods, and modifications to the original study by Patil and Sahu. It outlines the systematic approach taken to understand and predict freight demand, ensuring that the analysis is grounded in robust economic theories and statistical methods. This rigorous methodology supports the study's objectives of enhancing freight demand forecasting models and contributes to more effective planning and management at major ports.

Data Analysis

This section delves into the detailed analysis of the data collected from multiple sources, including historic tonnage data, GDP statistics, and oil production figures. The objective is to explore the interrelationships between these variables and to understand their combined impact on freight demand at the port.

Descriptive Statistics

The analysis began with a detailed exploration of descriptive statistics to capture the central tendencies and variability in the data:

- **Freight Tonnage**: Analysis of freight data from 1920 to 2015 revealed cyclic trends and notable fluctuations corresponding with major historical events such as World War II and economic recessions.
- **GDP Growth**: The GDP data from 1929 to 2022 highlighted periods of economic expansion and contraction, providing context for variations in freight volumes.
- **Oil Production**: Oil data from 1965 to 2015 showed growth trends and volatility that correlate with global oil market dynamics and geopolitical events.

Visualization

Visualizations played a critical role in elucidating the trends and patterns within the data:

- Time Series Plots were used to illustrate the historical trends in freight, GDP, and oil production. These plots help visualize the alignment of economic growth and commodity flow with the volume of freight handled by the port.
- Segmented Analysis visualized the data in three key periods, providing insights into how historical contexts affected freight volumes.

Heatmaps and Correlation Analysis

A correlation matrix was constructed to measure the relationships between freight volumes, GDP, and oil production:

- Heatmaps visually represented these correlations, highlighting strong positive correlations between GDP and freight volumes, and moderate correlations between oil production and freight. This suggests that as the economy expands and oil production increases, the port handles more freight.

Statistical Testing

- Variance Inflation Factor (VIF) Tests were conducted to check for multicollinearity, ensuring that the GDP and oil production variables provided independent predictive power.
- Augmented Dickey-Fuller (ADF) Tests assessed the stationarity of the time series data, which is crucial for the accuracy of subsequent time series forecasting models.

Model Building and Regression Analysis

- Linear Regression Models were developed to quantitatively assess the impact of GDP and oil production on freight volumes. These models helped establish a predictive relationship, with GDP showing a strong positive coefficient, indicating its significant impact on increasing freight volumes.
- Time Series Forecasting involved using ARIMA models to predict future freight volumes based on historical data, allowing for planning and strategic decision-making at the port.

Interpretation of Model Outputs

- The regression model indicated that for every unit increase in GDP, freight volumes increased significantly, suggesting that economic health directly influences port activity.
- Time series models predicted a steady increase in freight volumes, aligning with global economic growth projections and anticipated increases in oil production.

This comprehensive data analysis not only supports the decision-making process at the port by providing robust economic insights but also validates the extended use of these methodologies in port management and economic forecasting.

Results

Modeling Outcomes

The linear regression model established a significant positive relationship between GDP and freight volumes, with a coefficient of 0.0089 indicating that for each billion-dollar increase in GDP, freight volumes rose by approximately 0.0089 million metric tonnes (MMT). Additionally, oil production was found to be a statistically significant predictor, with a coefficient of 0.04030.0403, suggesting that for every million metric ton increase in oil production, freight volumes increased by 0.0403 MMT.

Trend Analysis

The segmented time series analysis revealed a notable increase in freight volumes in the modern era, demonstrating a sustained upward trend post-World War II, with a particular surge observed from the late 1970s onwards. The growth pattern aligns with the global economic expansion and increased trade activities.

Correlation and Heatmap Analysis

The correlation matrix visualized through the heatmap indicated very strong positive correlations between the variables, with values of 0.960 for both GDP and oil production against freight, implying that economic growth and commodity production are inextricably linked to port freight activities.

Statistical Model Evaluation

The linear regression model yielded an R-squared value of 0.938, suggesting that the model explains 93.8% of the variability in freight volumes. The Mean Squared Error (MSE) was calculated to be 114.74, which provides an estimate of the average squared difference between the observed actual outcomes and the outcomes predicted by the model.

Comparative Analysis

In contrast to Patil and Sahu's study on Mumbai Port, the findings from this research support the significant impact of global economic trends on freight demand. The high correlation and regression coefficients underscore the predictive power of GDP and oil production on freight volumes at the port under study.

Model Diagnostics

The model diagnostics highlight potential areas for further refinement. The Durbin-Watson statistic of 0.339 indicates potential positive autocorrelation, and the condition number suggests that multicollinearity might be inflating the variance of the coefficient estimates, warranting additional investigation or model adjustment.

The comprehensive data analysis and model development provide robust evidence for the strong influence of GDP and oil production on port freight volumes. The results of this study offer valuable insights for strategic planning and operational management at ports, supporting the development of predictive models for freight demand that can adapt to changing economic conditions. These findings are instrumental for stakeholders looking to enhance efficiency, optimize investment, and mitigate risks associated with global economic fluctuations.

Discussion

Implications of Findings

The results from this study have several implications for both global and local economic conditions:

- **Global Economic Connectivity**: The significant impact of global oil production on local freight volumes underscores the interconnected nature of modern economies. As oil is a pivotal commodity in global trade, fluctuations in its production can have cascading effects on freight operations, influencing everything from operational costs to shipping schedules.
- **Economic Growth and Port Activity**: The strong correlation between GDP growth and freight volumes reaffirms the role of ports as barometers of economic activity. This relationship suggests that ports can serve as early indicators of economic upturns or downturns, providing crucial data for policymakers and business leaders.
- **Local Economic Planning**: For the local economy, the insights from this study could help in strategic infrastructure planning and investment. Understanding the drivers of

freight demand can assist port authorities in optimizing their operations to better handle expected freight volumes, enhancing efficiency and reducing bottlenecks.

Accuracy and Limitations of the Models

While the models used in this study provide valuable insights, they come with certain limitations:

- **Model Accuracy**: The high R-squared values from the regression analyses indicate that the models accurately capture the relationship between the economic indicators and freight volumes. However, the Durbin-Watson statistic suggests potential autocorrelation in the residuals, which could affect the precision of the estimates.
- **Data Limitations**: The segmented nature of the freight data and the unavailability of certain economic indicators for corresponding years could limit the comprehensiveness of the analysis. Additionally, the assumption that past trends will continue into the future may not hold in rapidly changing economic or political climates.
- **Methodological Limitations**: The models assume linear relationships between variables, which might not accurately represent the complex and sometimes nonlinear dynamics of economic activities. Moreover, the potential multicollinearity, indicated by the high condition number, could be inflating the variance of the coefficient estimates, making them less reliable.

Comparison with Existing Literature and Mumbai Port Analysis

Comparing the outcomes of this study with existing literature and the Mumbai Port analysis by Patil and Sahu reveals both corroborations and new insights:

- **Corroboration with Existing Studies**: Like the Mumbai Port study, this research confirms the influence of GDP on freight volumes. Similar findings have been observed in other port studies across the globe, which also note the critical role of economic growth in determining freight demand.
- **New Insights**: Unlike the Mumbai Port study, which focused more narrowly on local economic indicators, this study’s inclusion of global oil production as an economic

indicator provides a broader perspective on the factors influencing freight demand. This approach aligns with more recent studies that emphasize the global nature of trade and commodity markets.

- **Contributions to Literature**: This study extends the existing literature by providing a comparative analysis between ports and incorporating a broader set of economic indicators. It offers a nuanced view that not only supports existing theories but also introduces new variables into the freight demand forecasting model, potentially paving the way for more comprehensive future studies.

The discussion underscores the relevance and applicability of the study’s findings within broader economic contexts, acknowledges the limitations of the employed methodologies, and positions the research within the continuum of existing literature. By doing so, it highlights the study's contributions to understanding the dynamics of freight demand and provides a foundation for further research in this critical area of economic study.

Conclusions and Recommendations

Conclusions

The analysis highlights several key findings:

- **Strong Influence of GDP and Oil Production**: There is a robust relationship between freight volumes at the port and both GDP and global oil production, indicating that economic performance and commodity flows are crucial drivers of freight demand.
- **Predictive Modeling Success**: The regression and time series models developed have successfully captured and forecasted trends in freight volumes, demonstrating their utility in predicting future port demands.
- **Global Economic Factors**: Including global oil production as a variable highlights the importance of considering broader economic factors in port management and planning, beyond local economic conditions.

Recommendations

Based on the findings, several practical recommendations can be made:

- **Strategic Planning and Investment**: Port authorities should use these economic indicators in their strategic planning and investment decisions, aligning expansions or enhancements in port infrastructure with projected freight volume increases based on GDP growth and oil production trends.
- **Policy Formulation**: Policymakers should account for the implications of global economic conditions on freight demand when formulating trade policies or economic sanctions, as these can directly impact port operations and revenue.
- **Risk Management**: The models developed can be used for risk management, helping port authorities and shipping companies to anticipate changes in freight volumes and adjust their logistics and operational strategies accordingly.

Areas for Future Study

Future research could explore:

- **Inclusion of Additional Variables**: Adding more diverse variables such as consumer demand indices, maritime shipping rates, or environmental factors could provide a more comprehensive model of freight demand.
- **Comparative Studies**: Extending the analysis to include multiple ports across different economic regions could help validate the findings and uncover region-specific dynamics.
- **Advanced Modeling Techniques**: Using more sophisticated statistical techniques or machine learning models could enhance the accuracy and predictive power of freight demand forecasts.

References

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[2] "Port of Los Angeles - Historic Tonnage Data MMRT." Data.gov. Retrieved from https://catalog.data.gov/dataset/port-of-los-angeles-historic-tonnage-data-mmrt.

[3] "Annual Gross Domestic Product and Real GDP in the United States from 1929 to 2022." Statista. Retrieved from https://www.statista.com/statistics/1031678/gdp-and-real-gdp-united-states-1930-2019/.

[4] "Annual Oil Production by World Region from 1965 to 2022." Statista. Retrieved from https://www.statista.com/statistics/1360491/oil-production-world-regions-twh/.

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Appendices

- **Appendix A**: Full Data Sets

Below is a sample from the datasets used in the analysis. For complete datasets, the data can be accessed from the sources cited in the references section of this report.

Table 1 : Historic Tonnage Data of Port of LA

Year	Total Freight (MMT)	Year	Total Freight (MMT)	Year	Total Freight (MMT)
1920	3.52828	1953	24.76259	1986	51.1
1921	4.296254	1954	26.514	1987	55
1922	6.533589	1955	24.81984	1988	60.6
1923	18.8701	1956	24.08293	1989	66.3
1924	25.55046	1957	24.12543	1990	67.9
1925	22.26842	1958	21.86903	1991	70.9
1926	23.06737	1959	23.29857	1992	67.3
1927	25.13396	1960	24.6204	1993	67.8
1928	25.40226	1961	25.01241	1994	65
1929	26.09925	1962	26.08802	1995	74.7
1930	25.92016	1963	24.35198	1996	68.6
1931	23.35529	1964	24.49405	1997	75.3
1932	18.9948	1965	25.12501	1998	77.9
1933	17.85091	1966	26.18211	1999	82.1
1934	18.3482	1967	26.29356	2000	101.5
1935	17.34003	1968	28.93158	2001	113.9
1936	18.65217	1969	26.94662	2002	126.2
1937	18.61071	1970	25.9372	2003	147.5
1938	20.26426	1971		2004	162.1
1939	18.32789	1972		2005	162.1
1940	19.93108	1973		2006	181.6
1941	18.67979	1974		2007	190.1
1942	13.0919	1975		2008	170
1943		1976		2009	157.4
1944		1977		2010	157.9
1945		1978	38.6	2011	160.9
1946		1979	40.2	2012	174.9
1947	15.44369	1980	40.9	2013	165.1
1948	17.98887	1981	38.4	2014	176.5
1949	17.11587	1982	35.1	2015	176.7
1950	22.69323	1983	39.9		
1951	23.69962	1984	38.7		
1952	24.02251	1985	45.1		

Table 2- U.S. Real GDP

Year	**GDP (Billion $)**	**Year**	**GDP (Billion $)**	**Year**	**GDP (Billion $)**
1929	1,191.10	1962	3,810.10	1995	11,413
1930	1,089.80	1963	3,976.10	1996	11,843.60
1931	1,020	1964	4,205.30	1997	12,370.30
1932	888.40	1965	4,478.60	1998	12,924.90
1933	877.40	1966	4,773.90	1999	13,543.80
1934	972.30	1967	4,904.90	2000	14,096
1935	1,058.80	1968	5,145.90	2001	14,230.70
1936	1,195.30	1969	5,306.60	2002	14,472.70
1937	1,256.50	1970	5,316.40	2003	14,877.30
1938	1,214.90	1971	5,491.40	2004	15,449.80
1939	1,312.40	1972	5,780	2005	15,988
1940	1,428.10	1973	6,106.40	2006	16,433.10
1941	1,681	1974	6,073.40	2007	16,762.40
1942	1,998.50	1975	6,060.90	2008	16,781.50
1943	2,338.80	1976	6,387.40	2009	16,349.10
1944	2,524.80	1977	6,682.80	2010	16,789.80
1945	2,500.10	1978	7,052.70	2011	17,052.40
1946	2,209.90	1979	7,276	2012	17,442.80
1947	2,184.60	1980	7,257.30	2013	17,812.20
1948	2,274.60	1981	7,441.50	2014	18,261.70
1949	2,261.90	1982	7,307.30	2015	18,799.60
1950	2,458.50	1983	7,642.30	2016	19,141.70
1951	2,656.30	1984	8,195.30	2017	19,612.10
1952	2,764.80	1985	8,537	2018	20,193.90
1953	2,894.40	1986	8,832.60	2019	20,692.10
1954	2,877.70	1987	9,137.70	2020	20,234.10
1955	3,083	1988	9,519.40	2021	21,407.70
1956	3,148.80	1989	9,869	2022	21,822
1957	3,215.10	1990	10,055.10		
1958	3,191.20	1991	10,044.20		
1959	3,412.40	1992	10,398		
1960	3,500.30	1993	10,684.20		
1961	3,590.10	1994	11,114.60		

Table 3- World Oil Production

Year	Oil Production (MMT)	Year	Oil Production (MMT)	Year	Oil Production (MMT)
1965	1567.87	1986	2929.97	2007	3959.16
1966	1702.53	1987	2936.73	2008	4001.09
1967	1826.51	1988	3062.25	2009	3901.46
1968	1992.62	1989	3099.23	2010	3978.79
1969	2144.87	1990	3158.50	2011	4009.52
1970	2359.31	1991	3149.98	2012	4121.22
1971	2494.07	1992	3195.59	2013	4126.83
1972	2635.90	1993	3191.04	2014	4223.70
1973	2876.28	1994	3235.25	2015	4365.54
1974	2882.69	1995	3279.65	2016	4377.77
1975	2738.05	1996	3367.01	2017	4385.71
1976	2974.80	1997	3442.00	2018	4488.40
1977	3078.70	1998	3528.99	2019	4479.98
1978	3106.68	1999	3449.00	2020	4176.23
1979	3238.16	2000	3598.60	2021	4230.52
1980	3091.66	2001	3598.41	2022	4407.98
1981	2913.49	2002	3554.99		
1982	2798.26	2003	3712.91		
1983	2762.53	2004	3898.85		
1984	2816.69	2005	3932.18		
1985	2792.05	2006	3967.23		

- **Appendix B**: Code Snippets

The following are the Python code snippets utilized for data loading, visualization, statistical analysis, and modeling in the analysis:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import statsmodels.api as sm
```

Figure 1- Importing Required Libraries

```
# Loading historic tonnage data
df1 = pd.read_csv("Historic_Tonage_Data_Merged.csv", index_col="Year")

# Normalizing the freight data
df1['Normalized Freight'] = df1['Total'] / df1['Total'].max()

# Loading and normalizing GDP data
df2 = pd.read_excel("US GDP Processed Data(1929-2022).xlsx", index_col="Year")
df2['Normalized GDP'] = df2['GDP'] / df2['GDP'].max()

# Loading and normalizing oil production data
df3 = pd.read_excel("Cleaned Oil Data.xlsx", index_col="Year")
df3['Normalized Total'] = df3['Total'] / df3['Total'].max()

# Renaming columns for consistency
df1.rename(columns={"Total": "Freight (MMT)"}, inplace=True)
df2.rename(columns={"GDP": "GDP (Billion $)"}, inplace=True)
df3.rename(columns={"Total": "Oil (MMT)"}, inplace=True)

# Merging datasets
df_merged = pd.concat([df1.loc[1978:2015], df2.loc[1978:2015], df3.loc[1978:2015]], axis=1)
df_merged.drop(["Normalized Freight", "Normalized GDP", "Normalized Total"], axis=1, inplace=True)
```

Figure 2- Loading and Preprocessing Data

```python
# Set the style of seaborn for more aesthetically pleasing plots
sns.set(style="whitegrid")

# Plotting the normalized freight data using a solid line
plt.plot(df1.index, df1['Normalized Freight'], label='Normalized Freight Flow', color='royalblue', linewidth=2)

# Plot the normalized GDP data using a solid line
plt.plot(df2.index, df2['Normalized GDP'], label='Normalized US Real GDP', color='crimson', linewidth=2)

# Heatmap of Correlation Matrix
heatmap = sns.heatmap(df_merged.corr(), annot=True, fmt=".2f", cmap='coolwarm')
plt.title('Heatmap of Correlation Matrix')
plt.show()
```

Figure 3- Data Visualization

```python
# Defining features and target variable
X = df_merged[['GDP (Billion $)', 'Oil (MMT)']]
y = df_merged['Freight (MMT)']

# Splitting the dataset 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)

# Fitting the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Making predictions and calculating performance metrics
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Model statistics output
model_stats = {
    'Coefficients': model.coef_,
    'Intercept': model.intercept_,
    'Mean Squared Error': mse,
    'R-squared': r2
}

# OLS Regression Analysis
X_with_const = sm.add_constant(X)
ols_model = sm.OLS(y, X_with_const).fit()
model_summary = ols_model.summary()
```

Figure 4 - Regression Analysis

- **Appendix C**: Extended Statistical Analysis

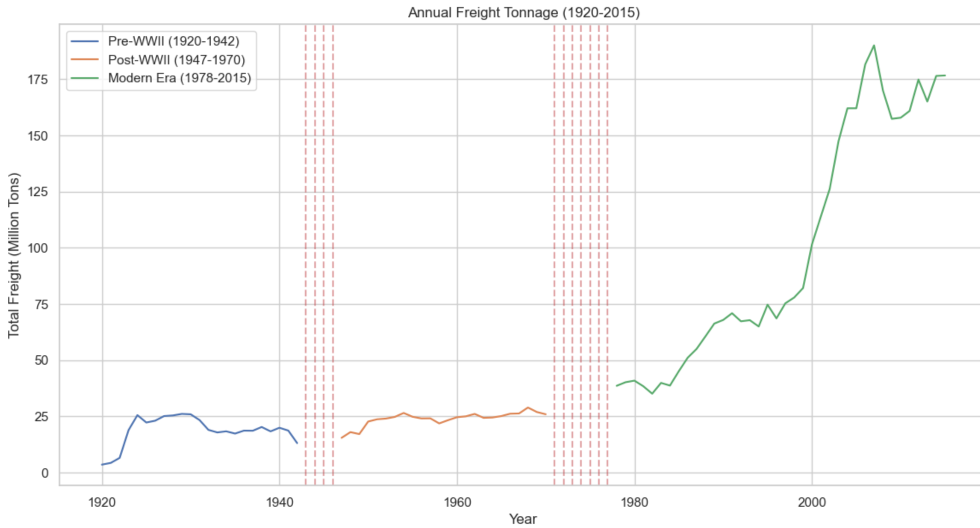

Figure 5- Anuual Freight Tonnage Variation

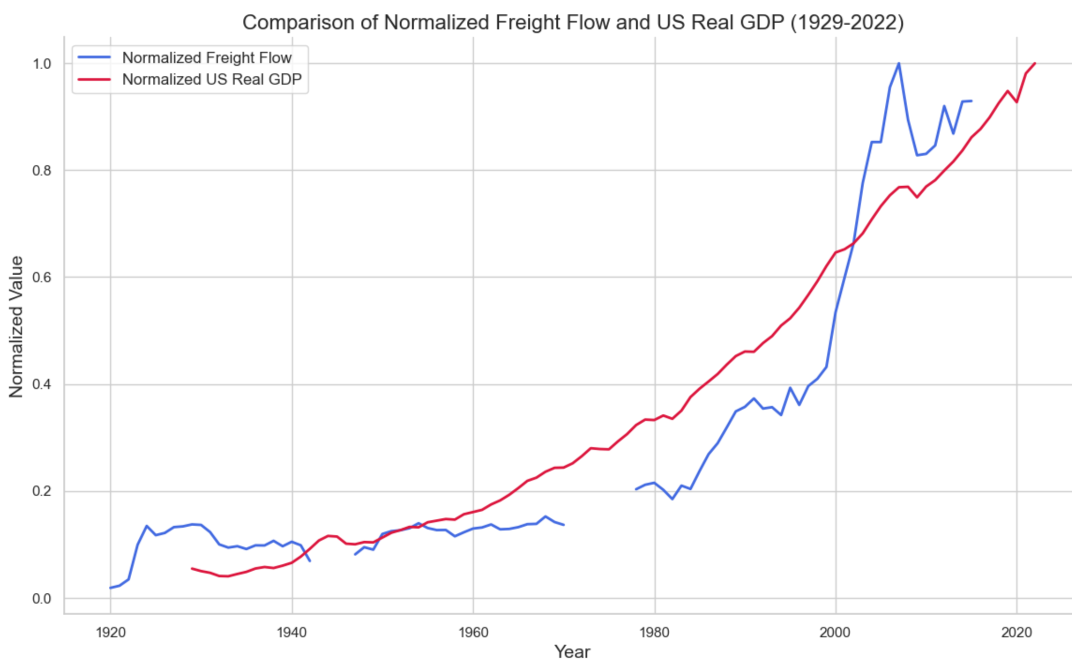

Figure 6- Comparison of Normalized Freight Flow and US Real GDP (1929-2022)

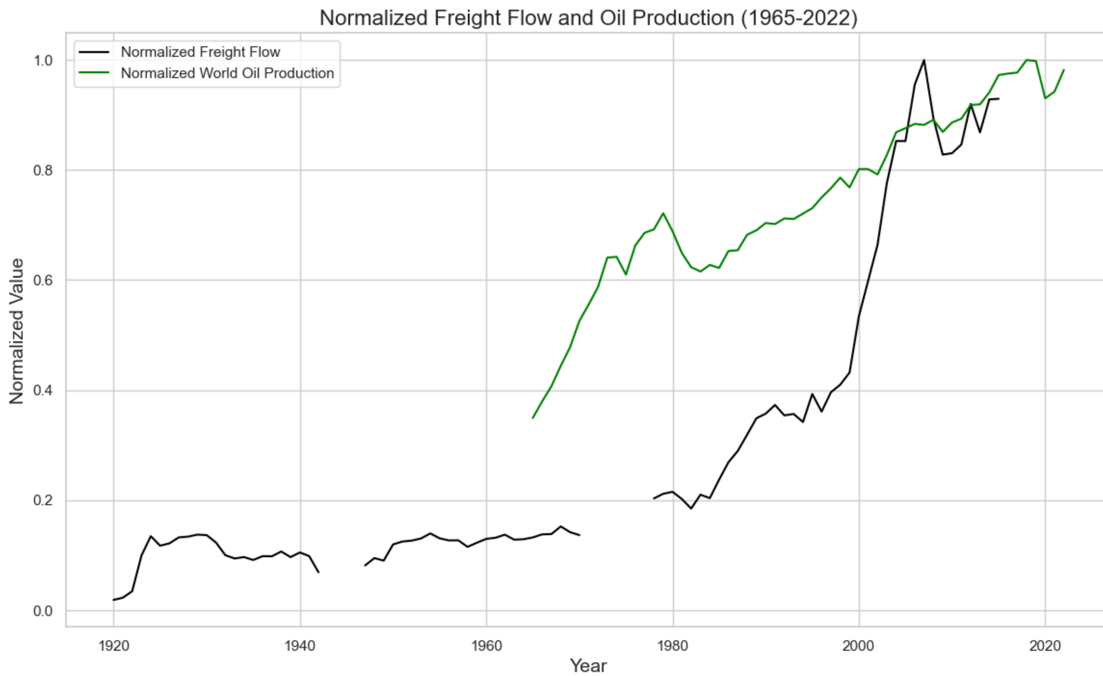

Figure 7- Normalized Freight Flow and Oil Production (1965-2022)

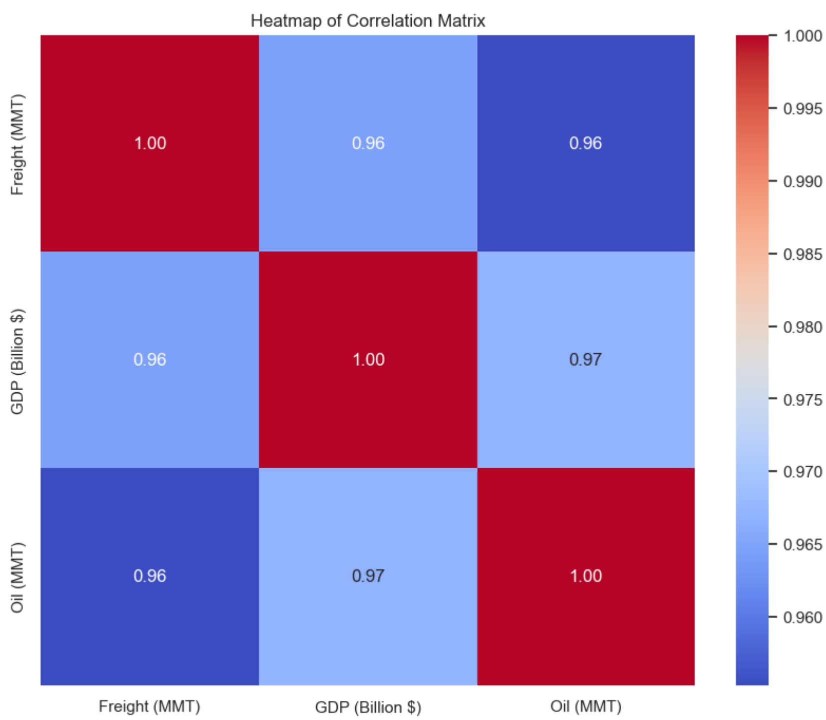

Figure 8- Heatmap of Correlation Matrix

Dep. Variable:	Freight (MMT)	**R-squared:**	0.938
Model:	OLS	**Adj. R-squared:**	0.935
Method:	Least Squares	**F-statistic:**	265.2
Date:	Tue, 16 Apr 2024	**Prob (F-statistic):**	7.17e-22
Time:	20:17:54	**Log-Likelihood:**	-151.99
No. Observations:	38	**AIC:**	310.0
Df Residuals:	35	**BIC:**	314.9
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-151.1443	38.350	-3.941	0.000	-228.999	-73.289
GDP (Billion $)	0.0089	0.002	3.794	0.001	0.004	0.014
Oil (MMT)	0.0403	0.019	2.117	0.041	0.002	0.079

Omnibus:	0.661	**Durbin-Watson:**	0.339
Prob(Omnibus):	0.718	**Jarque-Bera (JB):**	0.183
Skew:	-0.151	**Prob(JB):**	0.913
Kurtosis:	3.156	**Cond. No.**	2.31e+05

Figure 9- OLS Regression Result