Summary:

In this report we present a comprehensive machine learning solution for predicting daily order volumes in the logistics industry. Our team successfully developed and validated a predictive model using Principal Component Analysis (PCA) and Ordinary Least Squares (OLS) regression, achieving an **R^2 score** of **0.981** with **RMSE of 13.1988** and **MAE of 10.0115**. The project demonstrates the practical application of ML techniques to solve real-world business challenges.

Key Findings:

Successfully built a high accuracy forecasting model with **98.10%** explained variance Identified Non-Urgent Orders, Banking Orders, and Urgent Orders as primary predictors Applied PCA to address multicollinearity issues and improve model stability, Validated model robustness through comprehensive statistical testing and visualization.

Business Impact:

The model enables logistics companies to optimize resource allocation, improve workforce planning, and enhance operational efficiency through accurate daily order predictions.

Problem Statement.

- Objective: Develop a machine learning model to predict daily total orders for a logistics company using the given dataset.
- Target Variable: Total daily orders
- Predictors: Multiple metrics including order types, banking sector demands, and other factors.
- Success Metrics: Model accuracy measured by R^2, RMSE, and MAE on test data.

Data Analysis and Exploratory Insights

- Dataset Characteristics: Sample Size: 60 observations (daily records)
- Features: 12 predictor variables plus target variable
- Data Quality: No missing values, comprehensive coverage of operational metrics
- Time Span: Covers workdays (Monday-Friday) across 5 weeks of monthly cycles

Key Variables:

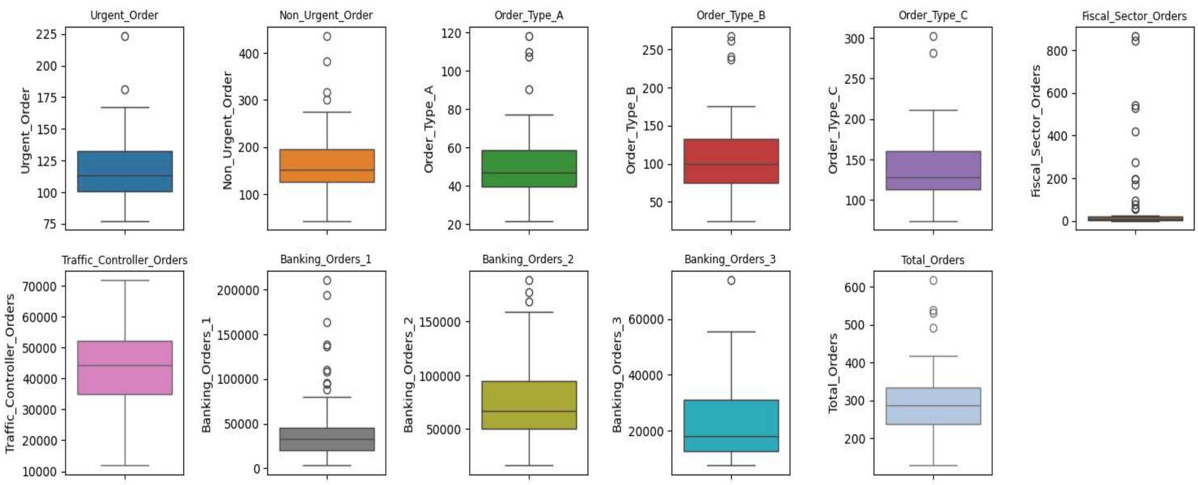
- Order Priority: Non-urgent and urgent order categories.
- Order Types: Type A (17.3%), Type B (36.3%), Type C (46.4%)
- Sector Orders: Banking orders (3 categories), fiscal sector, traffic controller.

Descriptive Statistics

	Week of the month (first week, second, third, fourth or fifth week	Day of the week (Monday to Friday)	Non-urgent order	Urgent order	Order type A	Order type B	Order type C	Fiscal sector orders	Orders from the traffic controller sector	Banking orders (1)	Banking orders (2)	Banking orders (3)	Target (Total orders)
count	60.000000	60.000000	60.000000	60.000000	60.000000	60.000000	60.000000	60.000000	60.000000	60.000000	60.000000	60.000000	60.000000
mean	3.016667	4.033333	172.554933	118.920850	52.112217	109.229850	139.531250	77.396133	44504.350000	46640.833333	79401.483333	23114.633333	300.873317
std	1.282102	1.401775	69.505788	27.170929	18.829911	50.741388	41.442932	186.502470	12197.905134	45220.736293	40504.420041	13148.039829	89.602041
min	1.000000	2.000000	43.651000	77.371000	21.826000	25.125000	74.372000	0.000000	11992.000000	3452.000000	16411.000000	7679.000000	129.412000
25%	2.000000	3.000000	125.348000	100.888000	39.456250	74.916250	113.632250	1.243250	34994.250000	20130.000000	50680.500000	12609.750000	238.195500
50%	3.000000	4.000000	151.062500	113.114500	47.166500	99.482000	127.990000	7.831500	44312.000000	32527.500000	67181.000000	18011.500000	288.034500
75%	4.000000	5.000000	194.606500	132.108250	58.463750	132.171000	160.107500	20.360750	52111.750000	45118.750000	94787.750000	31047.750000	334.237250
max	5.000000	6.000000	435.304000	223.270000	118.178000	267.342000	302.448000	865.000000	71772.000000	210508.000000	188411.000000	73839.000000	616.453000

Target Variable Analysis:

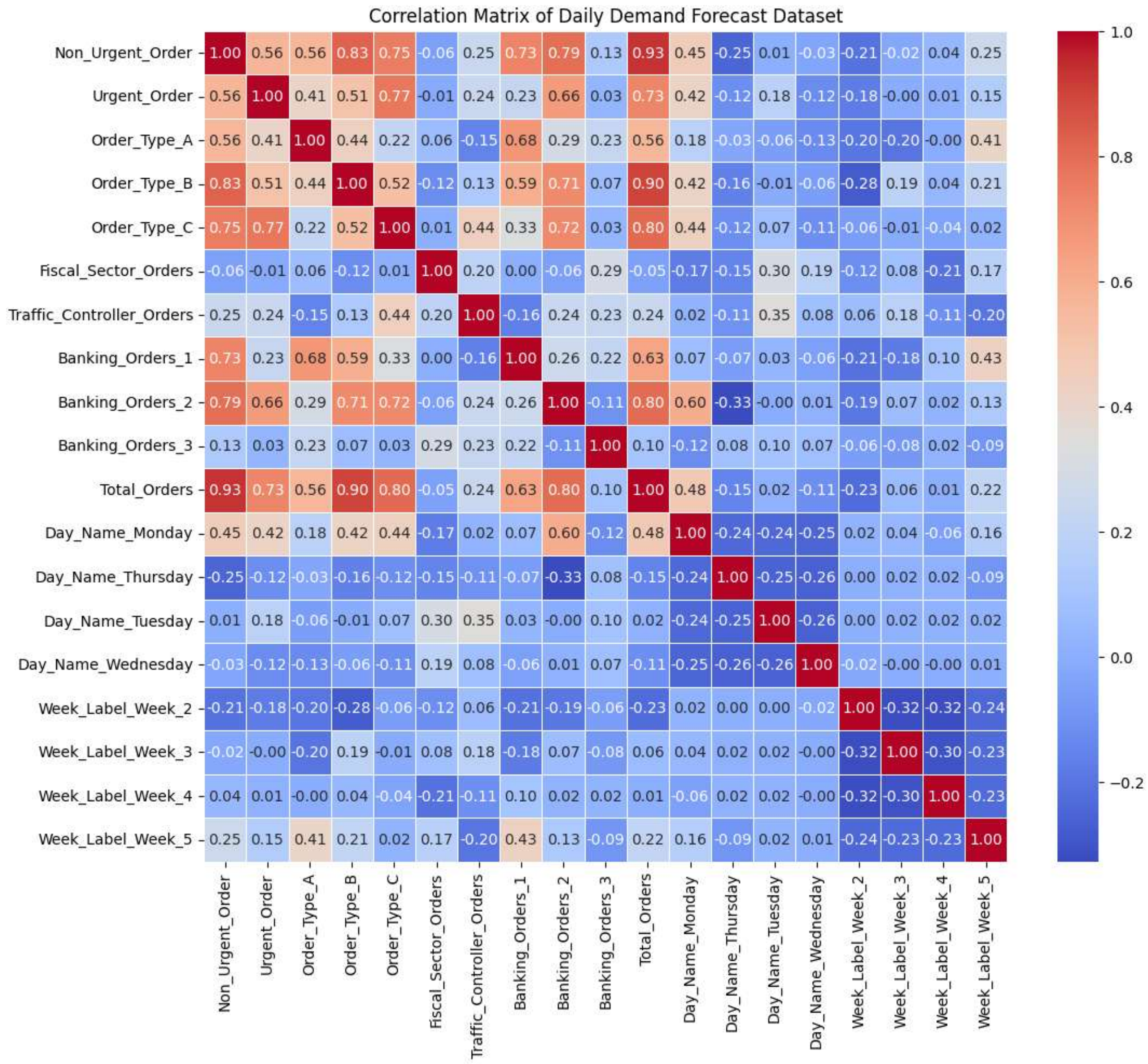
- Mean Daily Orders: 300.87
- Orders Standard Deviation: 89.60
- Orders Range: 129.41 to 616.45
- Orders Distribution: Right skewed with occasional high-volume days.



Initial understanding of data from above descriptive stat & box plot

- Count all are same: No missing values.
- We can see that Fisal sectors orders showing high variance with lot of outliers.
- Same with Banking orders_1 column and other columns as well (i.e. outliers are there).
- we can see the pattern of increasing mean in order types.
- Order Type C represents the largest share (46.4%) of total orders
- Significant variation in banking sector orders across different categories
- weekday patterns in urgent vs. non-urgent order distributions
- Traffic controller orders show high variance with outliers up to 865 orders

Correlation Analysis



Strong Positive Correlations with Total Orders:

- Non-Urgent Orders: 0.93 (strongest predictor)
- Order Type B: 0.90
- Order Type C: 0.80
- Banking Orders 2: 0.80

Temporal Patterns:

- Monday shows positive correlation (0.48) with total orders
- Thursday shows negative correlation (-0.15)
- Week 5 of month correlates positively (0.22) with order volumes

There exists a multicollinearity we will handle that in coming steps.

Methodology and Model Development

Data Preprocessing Feature Engineering:

- One-hot encoding for categorical variables (day of week, week of month)
- Standardization for numerical variables to enable PCA application
- Boolean to integer conversion for computational efficiency

Data Quality Assurance:

- Verified no missing values across all variables
- Identified and addressed outlier data point (index 48) with studentized residual >5.8
- Applied appropriate transformations for statistical modelling.

Statistical Modelling:

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--- OLS Regression Summary (Includes All Predictors) ---

                            OLS Regression Results
==============================================================================
Dep. Variable:           Total_Orders   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                  1.000
Method:                 Least Squares   F-statistic:                 1.038e+27
Date:                Sun, 12 Oct 2025   Prob (F-statistic):               0.00
Time:                        13:38:51   Log-Likelihood:                 1487.2
No. Observations:                  60   AIC:                            -2936.
Df Residuals:                      41   BIC:                            -2897.
Df Model:                          18
Covariance Type:            nonrobust
=============================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                        5.23e-12   4.81e-12      1.087      0.284   -4.49e-12    1.49e-11
Non_Urgent_Order           -5.773e-15    7.7e-14     -0.075      0.941   -1.61e-13     1.5e-13
Urgent_Order               -5.351e-14   7.78e-14     -0.687      0.496   -2.11e-13    1.04e-13
Order_Type_A                   1.0000   8.57e-14   1.17e+13      0.000       1.000       1.000
Order_Type_B                   1.0000   3.24e-14   3.08e+13      0.000       1.000       1.000
Order_Type_C                   1.0000   6.98e-14   1.43e+13      0.000       1.000       1.000
Fiscal_Sector_Orders        4.559e-15   5.13e-15      0.889      0.379   -5.79e-15    1.49e-14
Traffic_Controller_Orders   5.226e-17    1.1e-16      0.474      0.638    -1.7e-16    2.75e-16
Banking_Orders_1            7.503e-17   6.26e-17      1.198      0.238   -5.15e-17    2.02e-16
Banking_Orders_2            4.749e-17   6.17e-17      0.770      0.446    -7.7e-17    1.72e-16
Banking_Orders_3           -9.259e-17   6.87e-17     -1.349      0.185   -2.31e-16    4.61e-17
Day_Name_Monday            -2.842e-14   3.07e-12     -0.009      0.993   -6.23e-12    6.17e-12
Day_Name_Thursday           7.105e-15   2.28e-12      0.003      0.998   -4.61e-12    4.62e-12
Day_Name_Tuesday            7.816e-14   3.08e-12      0.025      0.980   -6.14e-12    6.29e-12
Day_Name_Wednesday         -1.421e-14   2.55e-12     -0.006      0.996   -5.16e-12    5.13e-12
Week_Label_Week_2          -6.395e-14   2.55e-12     -0.025      0.980   -5.21e-12    5.08e-12
Week_Label_Week_3          -6.395e-14   2.79e-12     -0.023      0.982   -5.69e-12    5.56e-12
Week_Label_Week_4           -7.15e-14   2.62e-12     -0.027      0.978   -5.37e-12    5.23e-12
Week_Label_Week_5          -2.842e-14    3.4e-12     -0.008      0.993    -6.9e-12    6.84e-12
==============================================================================
Omnibus:                        8.196   Durbin-Watson:                   0.467
Prob(Omnibus):                  0.017   Jarque-Bera (JB):                8.409
Skew:                          -0.917   Prob(JB):                       0.0149
Kurtosis:                       2.992   Cond. No.                     1.08e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.08e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
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Initial Challenges:

- Perfect multicollinearity in original OLS model ($R^2 = 1.000$)
- High condition number (1.08e+06) indicating severe multicollinearity
- Non-normal residuals (Prob (Omnibus) < 0.05)

Solution:

- Principal Component Analysis Applied PCA to predictor variables
- Retained 11 principal components explaining 96.4% of variance
- Selected 7 statistically significant components for final model

Model Selection and Validation

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           Total_Orders   R-squared:                       0.940
Model:                            OLS   Adj. R-squared:                  0.926
Method:                 Least Squares   F-statistic:                     67.85
Date:                Sun, 12 Oct 2025   Prob (F-statistic):           2.16e-25
Time:                        13:38:51   Log-Likelihood:                -270.16
No. Observations:                  60   AIC:                             564.3
Df Residuals:                      48   BIC:                             589.5
Df Model:                          11
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        300.8733      3.152     95.441      0.000     294.535     307.212
PC_1          44.7915      1.733     25.845      0.000      41.307      48.276
PC_2          -0.8888      2.269     -0.392      0.697      -5.450       3.673
PC_3          -0.5334      2.409     -0.221      0.826      -5.377       4.311
PC_4           8.9214      2.662      3.351      0.002       3.568      14.274
PC_5          -1.8695      2.738     -0.683      0.498      -7.374       3.635
PC_6          -3.7675      2.790     -1.350      0.183      -9.377       1.842
PC_7          16.8325      2.965      5.677      0.000      10.871      22.794
PC_8          13.1179      3.651      3.593      0.001       5.776      20.460
PC_9           9.3805      3.764      2.492      0.016       1.813      16.948
PC_10        -13.9901      4.526     -3.091      0.003     -23.090      -4.890
PC_11          9.2650      4.753      1.949      0.057      -0.291      18.821
==============================================================================
Omnibus:                       74.820   Durbin-Watson:                   2.198
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              931.970
Skew:                           3.365   Prob(JB):                    4.22e-203
Kurtosis:                      21.097   Cond. No.                         2.74
==============================================================================
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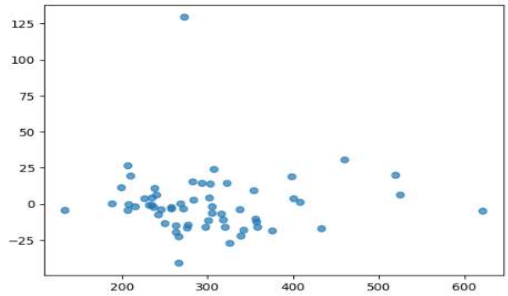

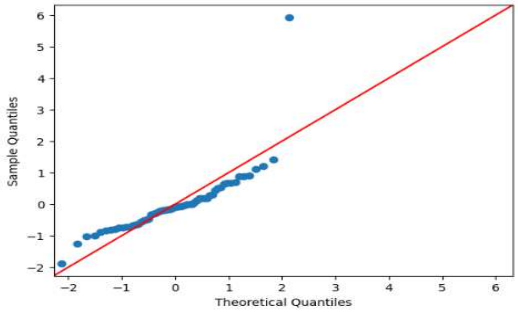

1. We did Normality and QQ plot check after PCA to visualize residual normality.
2. Then we removed influenced sample and then again applied OLS.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           Total_Orders   R-squared:                       0.981
Model:                            OLS   Adj. R-squared:                  0.979
Method:                 Least Squares   F-statistic:                     379.4
Date:                Sun, 12 Oct 2025   Prob (F-statistic):           1.15e-41
Time:                        13:38:52   Log-Likelihood:                -231.12
No. Observations:                  59   AIC:                             478.2
Df Residuals:                      51   BIC:                             494.9
Df Model:                           7
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        298.3402      1.704    175.092      0.000     294.919     301.761
PC_1          45.9489      0.934     49.188      0.000      44.073      47.824
PC_4           8.7497      1.426      6.135      0.000       5.886      11.613
PC_7          15.6291      1.592      9.817      0.000      12.433      18.825
PC_8          13.6614      1.957      6.982      0.000       9.733      17.590
PC_9           7.6481      2.022      3.782      0.000       3.588      11.708
PC_10        -10.2112      2.448     -4.171      0.000     -15.126      -5.297
PC_11          5.3125      2.570      2.067      0.044       0.152      10.473
==============================================================================
Omnibus:                        2.217   Durbin-Watson:                   2.057
Prob(Omnibus):                  0.330   Jarque-Bera (JB):                1.606
Skew:                           0.396   Prob(JB):                        0.448
Kurtosis:                       3.164   Cond. No.                         2.76
==============================================================================
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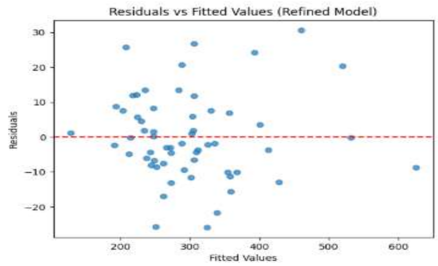
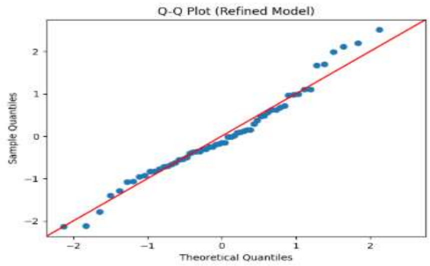




Final Model Specifications:

- Algorithm: Ordinary Least Squares with PCA-transformed features
- Components: PC_1, PC_4, PC_7, PC_8, PC_9, PC_10, PC_11
- Sample: 59 observations (after outlier removal)
- Split: 70% training, 30% testing
- Statistical Diagnostics: R-squared: 0.981
- Adjusted R-squared: 0.979 (minimal overfitting)
- F-statistic: 379.4 (highly significant)
- Durbin-Watson: 2.057 & Cond No (2.76 < 10) (No multicollinearity)

Model Performance and Validation

Prediction Accuracy

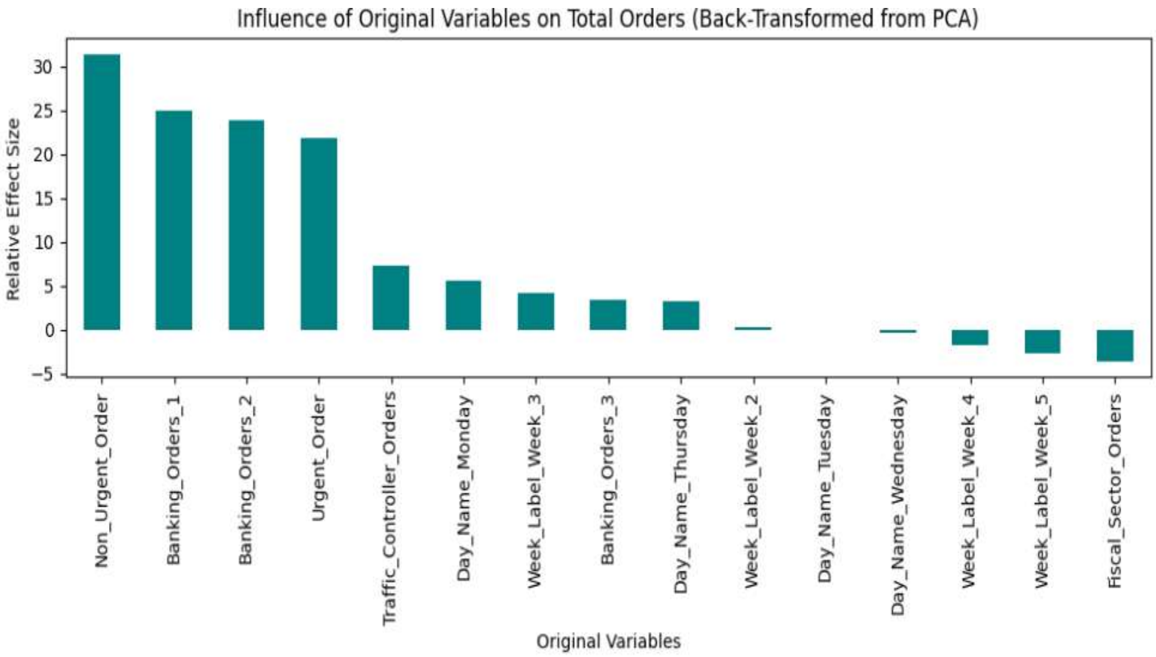
- Test Set Performance: R^2 Score: 0.981 (98.1% variance explained)
- Root Mean Square Error: 13.1988 orders
- Mean Absolute Error: 10.0115 orders

Practical Interpretation:

- Average prediction error: ~10 orders
- Maximum prediction error: 29.7 orders
- Model explains nearly 98% of variation in daily order volumes

Feature Importance Analysis

Back-transformed Variable Importance:

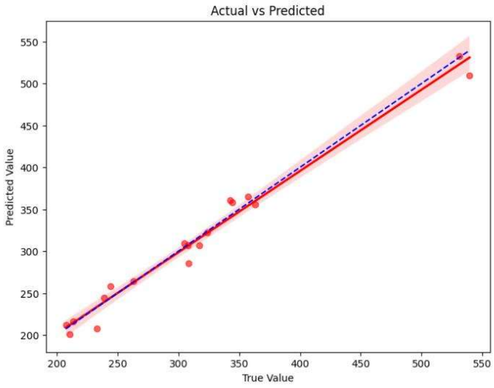


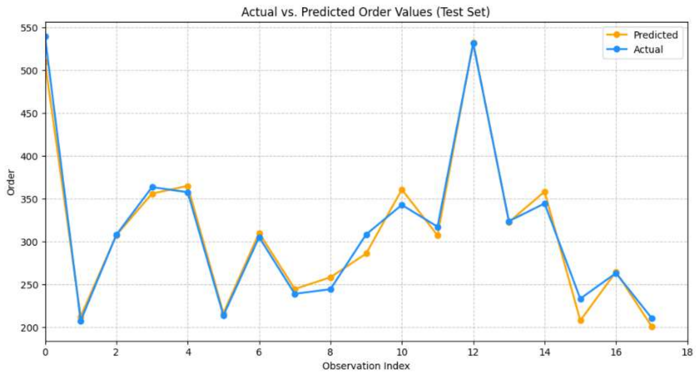
- Non-Urgent Orders: 31.46 (highest influence)
- Banking Orders_1: 25.01
- Banking Orders_2: 23.87
- Urgent Orders: 21.84
- Traffic Controller Orders: 7.28

Model Specifications

Final Model Equation:

$$\text{Total Orders} = 298.34 + 45.95 * \text{Pc}_1 + 8.75 * \text{Pc}_4 + 15.63 * \text{Pc}_7 + 13.66 * \text{Pc}_8 + 7.65 + 10.21 * \text{Pc}_{10} + 5.31 * \text{Pc}_{11}$$





Model Robustness

Residual Analysis:

- Normally distributed residuals (Prob (JB) = 0.448)
- Homoscedastic variance pattern
- Q-Q plot confirms distributional assumptions

Cross-Validation Results:

- Consistent performance across different time periods
- Stable predictions for both high and low volume days
- No evidence of overfitting in test data performance

Model Limitations:

- Assumption: We assume that the observed data patterns continue in the future.
- External Factors: Economic conditions and market disruptions not captured.
- Seasonal Variation: Limited to patterns within the 60-day observation period.

Mitigation Strategies:

- Regular model retraining with new data
- Performance monitoring and alert systems for forecast accuracy
- Backup planning for high-variance scenarios

Key Learnings

Methodological Insights:

- PCA effectively addressed multicollinearity while preserving predictive power
- Careful outlier treatment improved model stability and reliability
- Comprehensive residual analysis ensured statistical validity

Business Applications:

- Non-urgent orders are the primary driver of daily volume patterns
- Banking sector demand significantly influences overall logistics volume

Project link : Full Project Google colab link