Efficient Scheduling: Forecasting for Jakarta's 118 Ambulance

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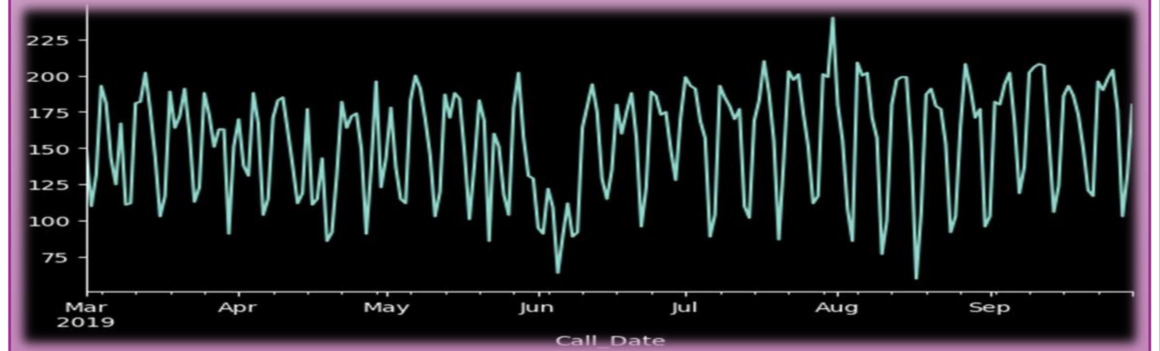
INTRODUCTION

This project employed Python to analyse past call data and predict future demand to improve the scheduling efficiency of Jakarta's 118 Charitable Ambulance Service. Python was employed in this research to examine past call data and predict forthcoming demand. The dataset collected between March & September 2019 formed the basis for constructing a predictive model capable of forecasting daily call volumes 2 month. The objective was to identify the best precise time series forecasting approach, evaluated by MSE, to aid the service in resource planning

INSIGHTS

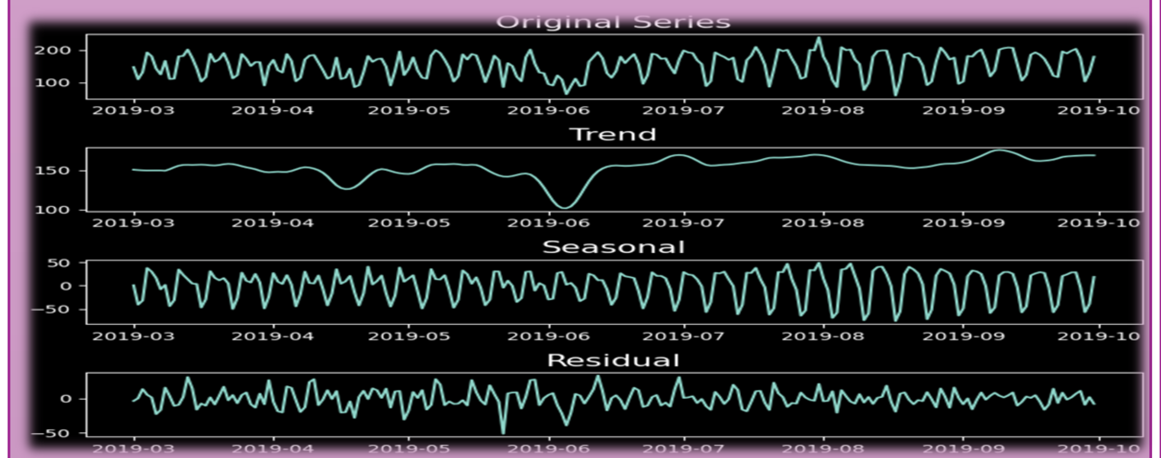
The Jakarta ambulance call volume data exhibits notable fluctuations, which are indicative of the inherent unpredictability that is characteristic of emergency services. The volatile data exhibits noticeable patterns of seasonality, characterised by periods of increased activity. However, the consistency of these peaks is not regularly observed, So deeper analysis and data is needed.



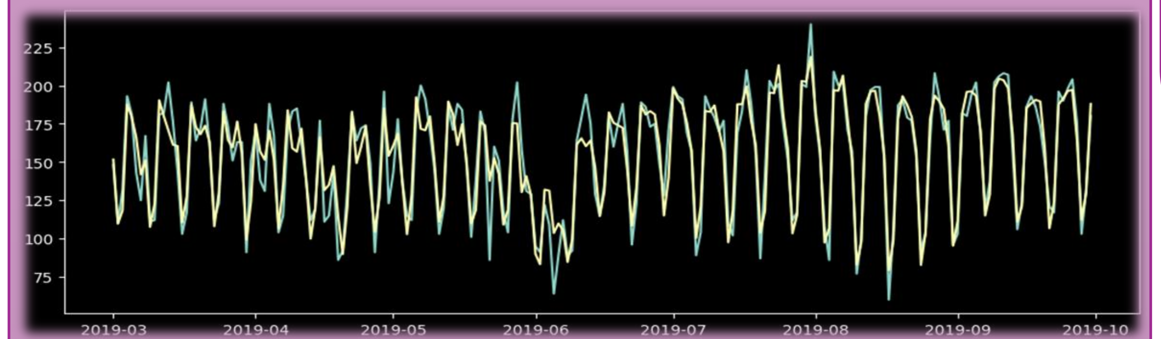
In the time series data displayed, which represents ambulance call volumes, an anomaly is highlighted as a significant deviation from the expected pattern. This deviation could be a sudden dip or spike in calls on a specific date that does not align with the seasonal or cyclical trends observed in the data. Such an anomaly stands out in the regular flow of data, indicating an unusual occurrence on that day, which could be aim to a specific, a typical event that disrupted the normal volume of ambulance services.

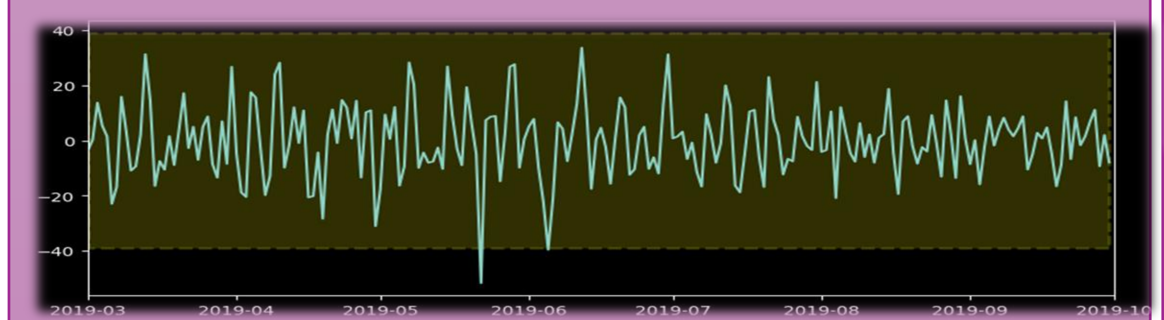
ANOMALY DETECTION

- To identify anomalies, we calculate the residual component's mean and standard deviation. Anomalies are data points that fall outside the expected range, which is typically 3 standard deviations from the mean. These points are potential outliers that deviate from the data's typical pattern.

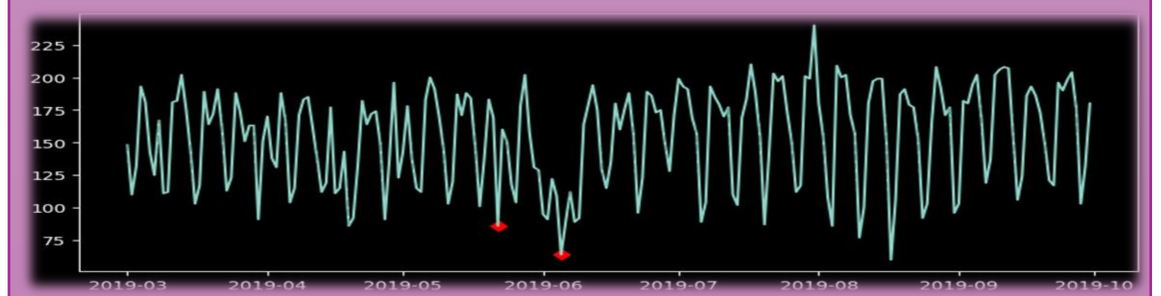


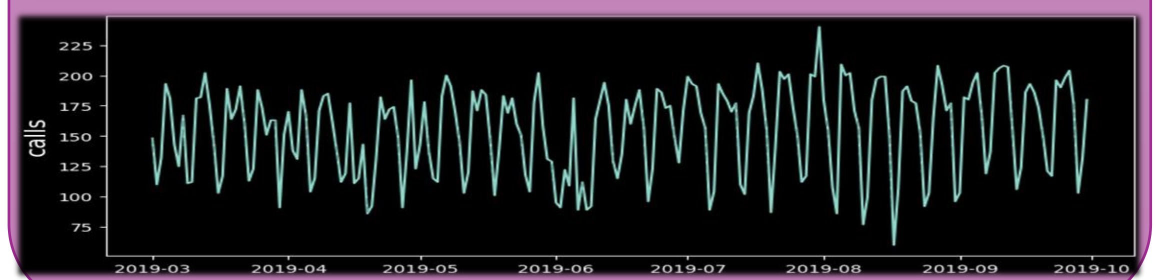
- We then calculate the mean, standard deviation of the residual component to identify anomalies. Anomalies are those data points that fall outside of the expected range, typically as 3 standard deviations from the mean. These points are potential outliers that don't follow the typical pattern of data.





- Anomalies in the first series' plot are marked with scatter points to make them easier to spot. For the dates identified as anomalies, the data points are replaced with the mean value of the same weekday from the dataset, excluding other anomalies.



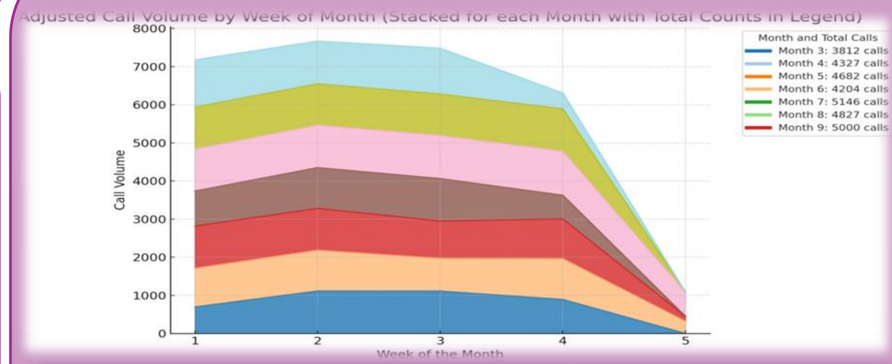


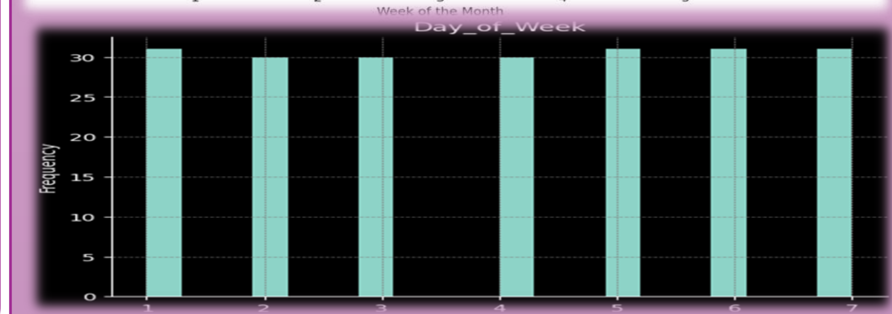
Numerical Summary

Statistic	Count	Mean	Std	Min	25%	50%	75%	Max	MAD
Value	214.0	153.76	37.42	60	119.25	163.5	183.75	240	32.43

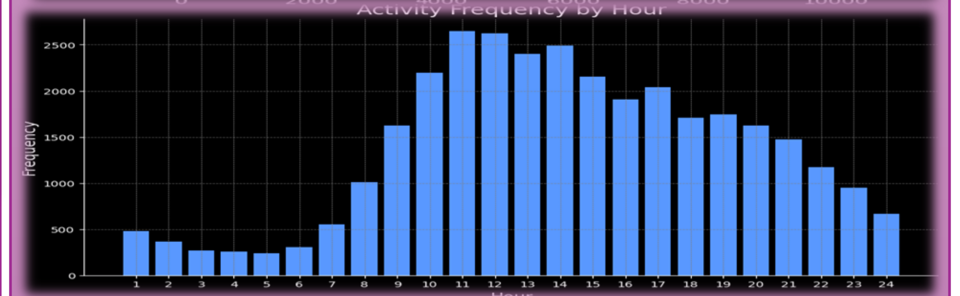
Based on the numerical summaries, the data shows a moderate daily call volume with an average of 153.76 and a consistent pattern of variability, as indicated by a Mean Absolute Deviation of 32.43.

Visual Insights





The stacked area chart shows a detailed breakdown of adjusted call volume by week for each month, highlighting fluctuations and trends over time. The associated legend measures the total monthly calls, for month-to-month comparisons. Meanwhile, the bar chart displays the frequency of calls on each day of the week. These visual tools are critical for resource planning because they identify peak periods and guide decisions on service availability and staffing requirements, ensuring readiness for high-demand days.



The bar chart shows call volumes separated by time of day, showing that afternoons are the busiest, with progressively fewer calls in the morning, evening, and night. This pattern indicates a daily rhythm in call activity, which could help staffing shifts. Meanwhile, the day-of-week chart shows that call frequency is highest midweek, with the lowest volumes recorded on weekends. Such insights are invaluable for scheduling because they focus attention on allocating more resources during busier midweek periods and afternoons when call volumes spike, ensuring peak readiness.

Stationarity Checks and Stabilizing Time Series

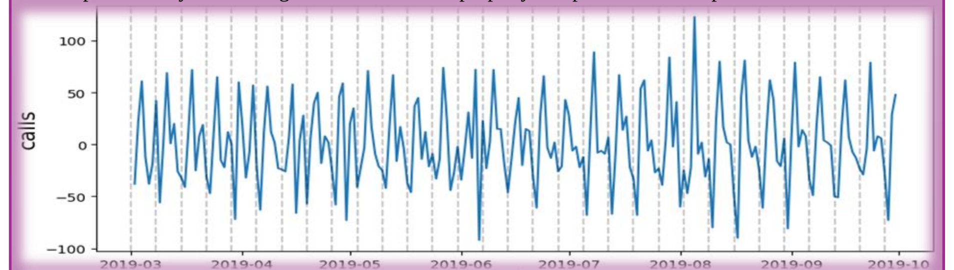
Stationarity in time series is crucial because it means that statistical properties like mean and variance remain constant over time, making the series predictable. It's a key assumption for many models to provide reliable forecasts and identify true relationships between variables without the influence of spurious trends or seasonality.

Test	Test Statistic	p-value	Critical Values (1%, 5%, 10%)
ADF	-2.1374	0.2297	-3.4636, -2.8762, -2.5746
KPSS	0.5832	0.0242	0.739 (1%), 0.574 (2.5%), 0.463 (5%), 0.347 (10%)

The ADF test statistic of -2.1374 with a p-value of 0.2297 suggests that we fail to reject the null hypothesis of a unit root, implying non-stationarity. The KPSS test statistic of 0.5832 with a p-value of 0.0242 indicates a rejection of the null hypothesis of stationarity at the 5% level. These tests collectively suggest the data may not be stationary.

Stabilizing Time Series by differencing

I used differencing to remove trends and cycles from the time series data, which could have affected the mean and variance's stability. This technique assisted in achieving stationarity, which is a necessary assumption for my forecasting models to function properly and provide reliable predictions.

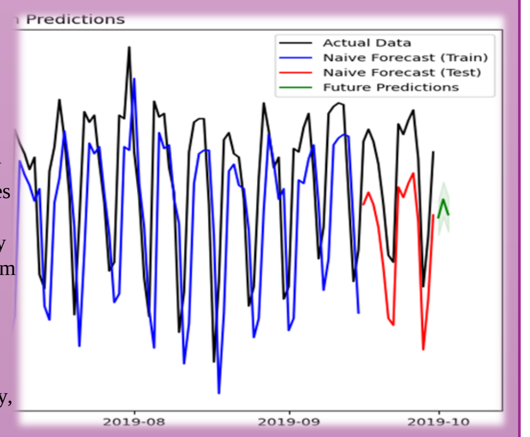


Test	Test Statistic	p-value	Critical Values at 1%, 5%, 10%
ADF	-6.3810	2.22e-08	-3.4636, -2.8762, -2.5746
KPSS	0.3344	0.1	0.739, 0.574, 0.463, 0.347

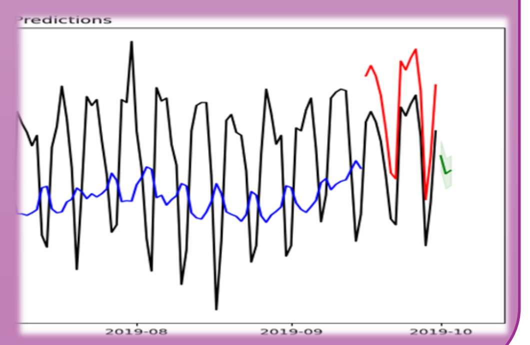
After differencing the data (taking the first difference), the ADF test yields a test statistic of -6.3810 with a p-value near zero, far below the critical values, indicating strong evidence against the null hypothesis of a unit root. This suggests the differenced series is stationary. Conversely, the KPSS test statistic of 0.3344 with a p-value of 0.1 fails to reject its null hypothesis, aligning with the ADF test result that no unit root is present, confirming stationarity.

Baseline model

After stabilising the time series data, I implemented the Naive Forecast model. This model bases future values on immediate past data with little to no shifts over time. To validate the model's predictions, the time series was split into training and testing sets: training data helps the model understand the pattern, while testing data, spanning a brief 15-day period, ensures the model is evaluated on its ability to predict in the short term. The plot compares actual values to the performance of the Naive Forecast, which closely matches the actual data during training but deviates slightly during testing, resulting in an **MSE of 1296**. This short-term testing period is critical in time series analysis for quick verifying model efficacy before moving on to longer-term predictions. The future predictions, marked in green with confidence bounds, suggest where the call volumes might head, with the shaded area representing potential variability, setting the stage for more advanced, predictive modelling.



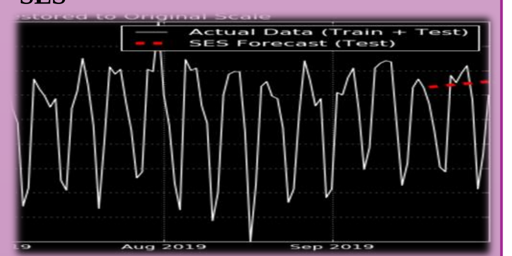
Next, I used a Moving Average forecast to smooth out short-term shifts and highlight long-term patterns. This method worked well, with the forecast nearly matching the actual data during the training phase. The test phase showed some variance, as measured by a **MSE of 950.69**, indicating a excellent match for such a simple model. With the training forecast in blue and the testing phase in red. Future forecasts, displayed in green, expand the forecast and include confidence intervals, indicating predicted call volume while accounting for potential variability. This model serves as a foundation for complex modelling, which will include other patterns detected in the time series.



Exploratory model

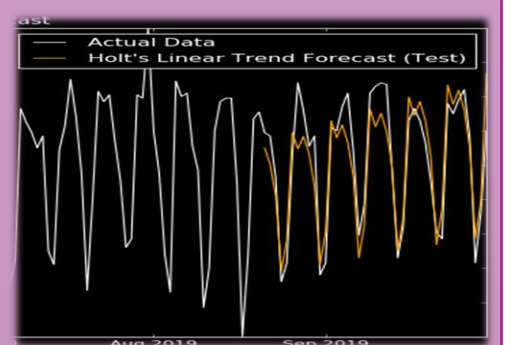
SES

After applying the Single Exponential Smoothing model, it becomes obvious that it is incapable of handling the trend and seasonality contained in the call volume data, as demonstrated by a high **MSE of 1850.5.** SES is a baseline model that makes no assumptions about trends or seasonalities. Given this constraint and the larger inaccuracy compared to other naive predictions, my next step is to use Holt's trend-corrected smoothing or the Holt-Winters approach to better model and anticipate the data with underlying seasonal and trend patterns.



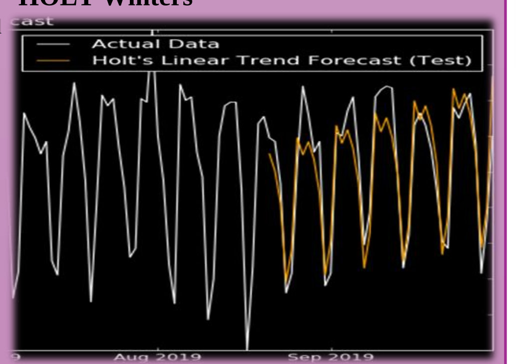
HOLT Linear

I used Holt's Linear Trend model for a 40-day timeframe, going past the previous 30-day window. With an **MSE of 241.70,** the wider dataset improves the model's trend-capture abilities. This improvement shows Holt's ability to project longer-term patterns, as indicated by the lower inaccuracy relative to previous forecasts. **The AIC & BIC scores, 1133.36 & 1145.97**, indicate a decent fit without overfitting, confirming the model's long-term performance. The model adjusted to the data's trend and seasonality, indicating its suitability for long-term forecasting. This method has proven effective, resulting in informed forecasts.



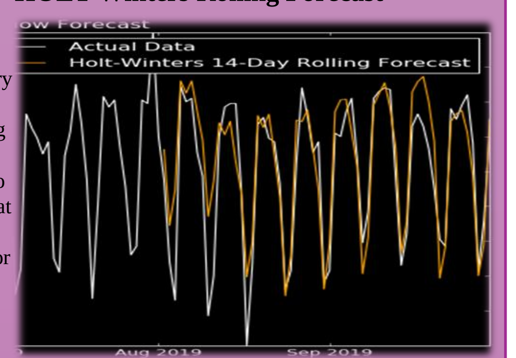
HOLT Winters

Using the Holt-Winters model with a multiplicative trend and additive seasonality fit the forecast of the call volume data, considerably improving accuracy with an **MSE of 181.29** and exceeding Holt's Linear model's **MSE of 241.70.** The multiplicative trend reflects the rising variability in data over time, whereas additive seasonality deals with constant seasonal swings, no matter the series level. The use of a damped trend reduces over-projections and reduces the expected trajectory. The **lower AIC and BIC values than Holt's, 1071.05 & 1108.89,** indicate Holt-Winters' efficiency in achieving a compromise between complexity & fit. This model combines seasonality & trend, showing its fit for datasets with unique cyclical behaviours and producing projections that closely resemble real-world patterns



HOLT Winters Rolling Forecast

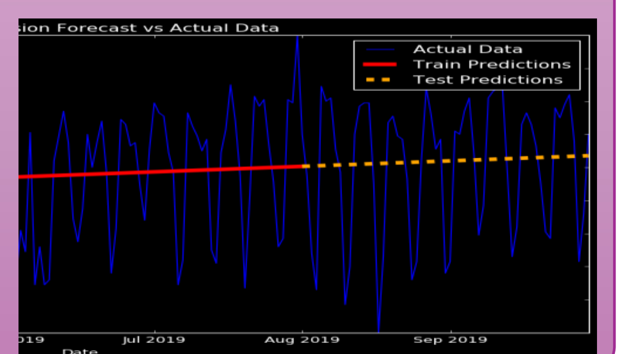
A rolling forecast proven to be a better strategy for projecting call volume over a two-month period. Using the Holt-Winters model, the rolling forecast required updating the forecasts every 10 days, allowing us to include the most recent data into the forecast. This approach is especially useful in rapidly changing situations because it enables the model to adjust to new trends and seasonal patterns.Rolling forecasts were conducted for two months, each using the most recent data available, ensuring that the model parameters were always updated to the newest conditions. This frequent adjustment is most likely the basis for the rolling forecast's **lower mean squared error (MSE),** indicating more accurate forecasts when compared to the traditional application of Holt's Linear and Holt-Winters when they are modelled for 2 month rather than 40-day time frame.



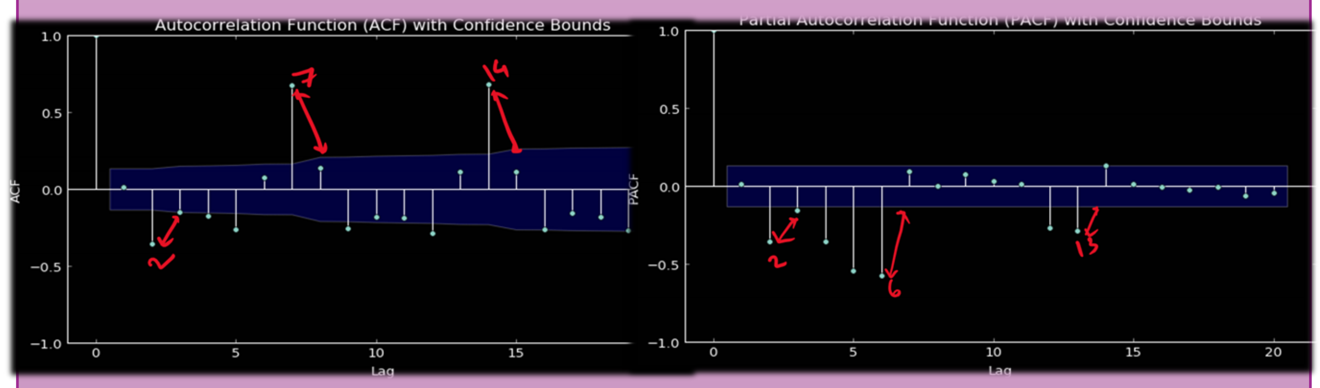
Technique	MSE
Holt Linear	3727.3
Holt-Winters	1747.7
Holt-Winters Rolling Forecast	410.1

Simple Linear regression

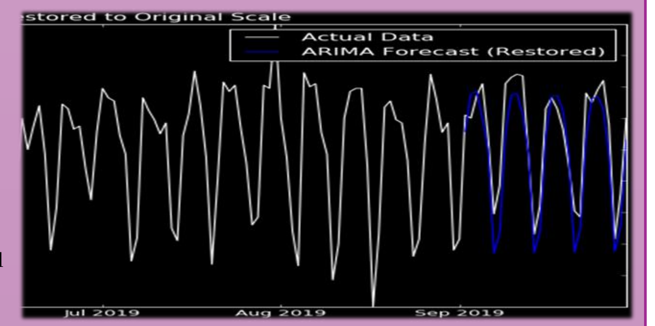
I used a basic linear regression model to forecast 'Call Volume', with a numerical time index as the predictor, analysing data from March to September 2019. The model's test phase resulted in a MSE of 847.20, indicating how well the model's predictions matched the test data. This implies that, while the model generalises well to test data, it does not capture all shifts, especially in the test set. The model's consistent performance across training and testing demonstrates its ability to capture the overall trend in 'Call Volume'.



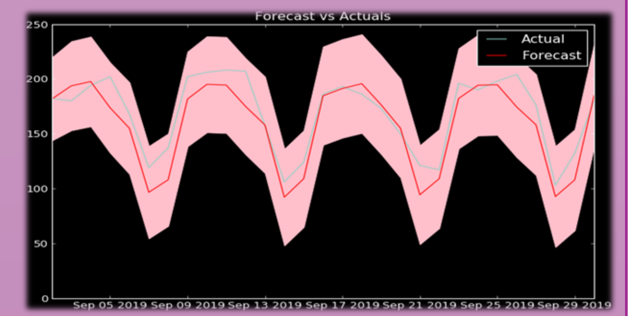
ARIMA



The ACF and PACF plots drove the selection of an ARIMA(6,0,7) model, with the ACF showing a strong weekly pattern showing a major drop at **7,14**. and the PACF identifying lags 2 and 6 as major autoregressive components. This model effectively exploits underlying temporal relationships, as indicated by a strong **MSE of 288.06** when restored to the original scale. The ARIMA model's predicting accuracy is further backed by decreased AIC and BIC values, indicating an appropriate balance of model complexity and data quality. This analytical approach, which is based on the autocorrelation features of time series, allows for precise forecasting that is closely related to actual trends and seasonal behaviours. As I am using differenced data and restoring it again before forecasting, thats why d=0

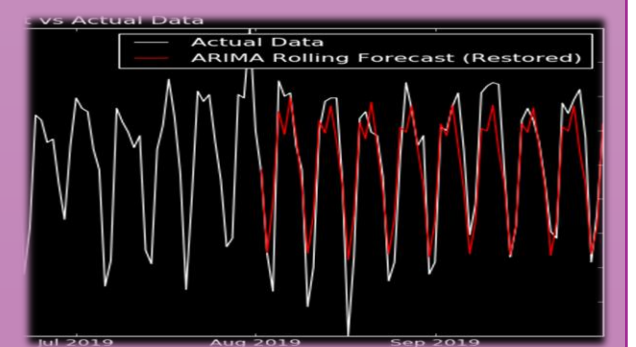


I used the SARIMA model with parameters **(6,0,2)x(2,1,5,7)** to adjust the call volume forecast. This method, which took advantage of the model's sensitivity to both seasonal and non-seasonal factors, resulted in an **MSE of 266.95**, a significant improvement over the prior ARIMA model. The forecast plot demonstrated the SARIMA's ability to capture the complexities of the data, as the model's predictions fit neatly inside the confidence intervals surrounding the actuals. The model's efficacy is further confirmed by its AIC and BIC values, which show a good match without overfitting. Through SARIMA, I had access to a more sophisticated level of time series analysis, resulting in forecasts that are not only more aligned with actual data but also more dependable for real decision-making situations.



ARIMA-SARIMA ROLLING FORECAST

I used a 10-day rolling **ARIMA** model on my dataset, which produced an **MSE of 379.15**, surpassing the normal ARIMA model's MSE of 691.27 for the **two-month** test data. This approach, which constantly incorporates new information, led in projections that were more responsive to current trends than the less regularly updated standard ARIMA. Compared to Holt-Winters rolling predictions, the ARIMA provided a feasible alternative that struck a balance between accuracy and adaptability. **Further refining my approach,** I applied a SARIMA rolling forecast model for a two-month period, which achieved an **even lower MSE of 255.60**. This confirms SARIMA's superiority in capturing the seasonal trends and complex patterns within the data. The results of the rolling forecasts across the three models are presented here:

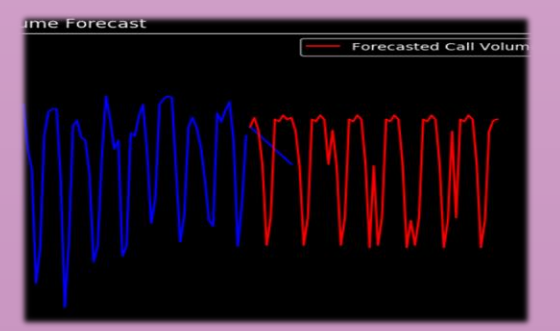


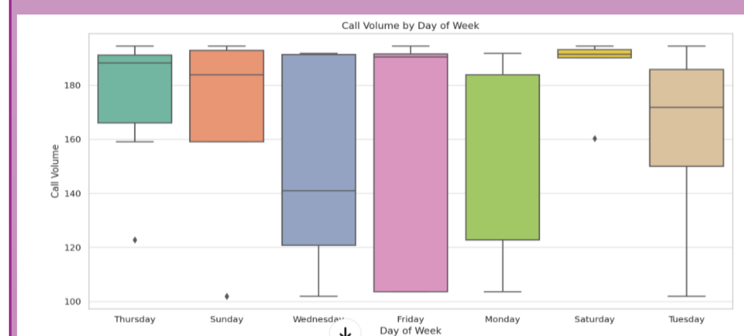
Model Type	MSE	AIC	BIC
Holt-Winters	410.08	1241.19	1281.01
ARIMA	379.15	1828.65	1878.34
SARIMA	255.60	1250.545	1297.612

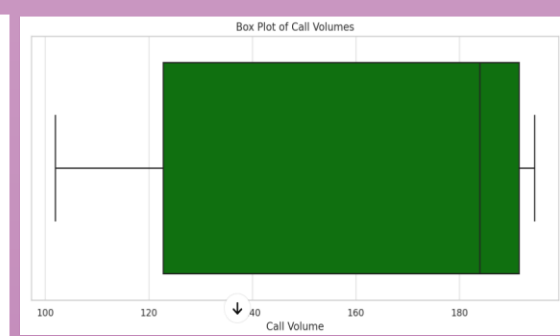
SARIMA emerges as the best model, with the **lowest MSE** indicating superior forecast accuracy and suitable **AIC and BIC** values that balance model complexity with data fit. This demonstrates SARIMA's robustness in capturing and forecasting complex time series information, making it an invaluable tool in situations where precision is critical for decision making.

Real time forecast on 2-month data

After finalizing with Sarima with appropriate parameters, I am moving to forecasts on a two-month dataset. Previously, I was using a naive rolling forecast approach. This meant moving the training data by 10 days rather than adding the forecasted value into future values. However, there is no observed data for the next timeframe, I created an actual rolling forecast that uses the forecasted value to estimate the next 10-day timeframe. This approach easily combines the expected values into forecasts, improving the accuracy of the predicted results. By adopting this technique, I hope to improve the predictability of the forecasting process, maintaining the model's forecasts closely match real data. This move is a step towards a more robust forecasting process, allowing for better informed decision-making based on the most accurate and up-to-date forecasts available.







These visualisations shed light on the unpredictability and dispersion of predicted call volumes. The box plot shows a somewhat constant call volume with few outliers, indicating persistent demand with rare spikes. The Day of the Week analysis reveals more complex trends, with call volumes peaking in the middle of the week and dropping off on weekends, indicating that services are in more demand throughout the workday. These insights are critical for the ambulance service's planning and resource allocation, allowing for strategic deployment of resources on busier days while pulling down on quieter ones to ensure efficiency and readiness.

Conclusion and Insights of work

Initial EDA revealed large volatility and seasonal variations in call volumes. Anomaly identification was critical to accurate forecasting. The study began with a Naive Forecast model and progressed to more advanced models such as Holt-Winters and SARIMA to better handle observable patterns and seasonalities. Holt-Winters enhanced accuracy through multiplicative trends and additive seasonality, however SARIMA outperformed because to its lower Mean Squared Error (MSE) and best fit. To improve predictions, a rolling forecast technique was adopted, which adapts to fresh data every two months. This strategy dramatically improved prediction predictability and dependability, allowing for more efficient resource allocation and rapid emergency response, illustrating the tremendous impact of sophisticated statistical techniques on operational efficiency in emergency services.