Duration and Vehicle Utilization Forecasting for Car Sharing

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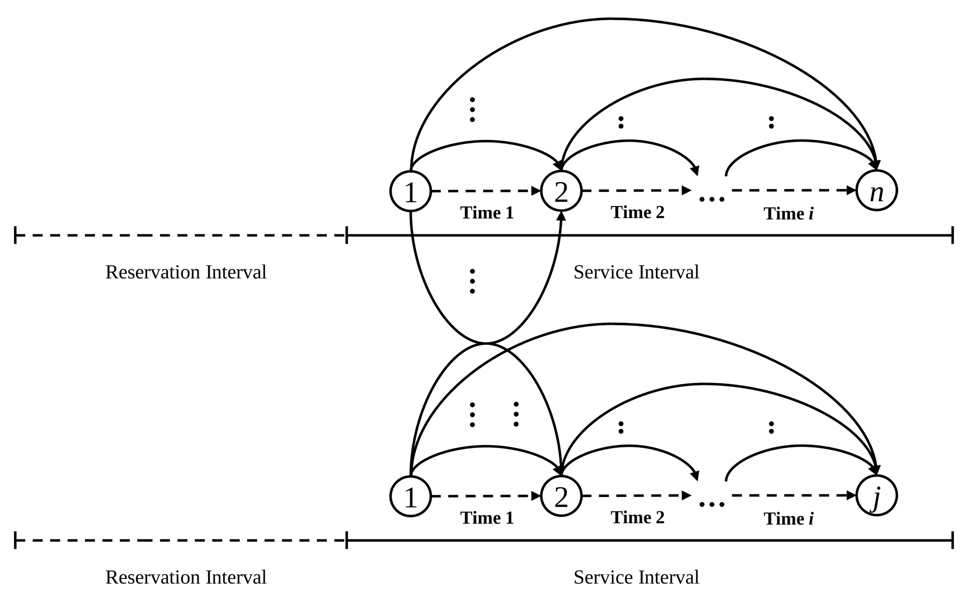
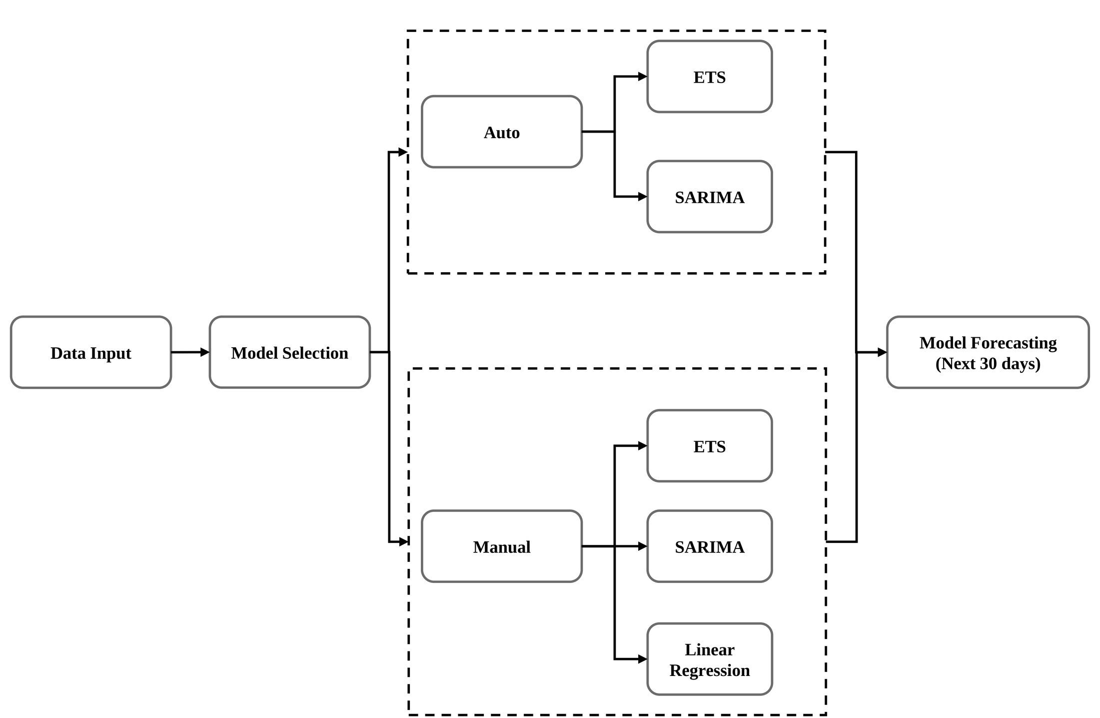
Introduction



- Accurate forecasting of duration is critical for optimizing vehicle utilization and reducing idle time.
- Cross-day bookings and mixed booking-usage records pose challenges for traditional models.
- We apply time series decomposition and proportional allocation to enhance city-level demand prediction.

Forecasting Models

- **Auto ETS:** Automatic Exponential Smoothing with additive trend ($y_t = l_t + b_t + \varepsilon_t$), no seasonal component, parameters auto-fitted.
- **Manual ETS:** Exponential Smoothing with additive trend and 7-day seasonality ($y_t = l_t + b_t + s_{t-7} + \varepsilon_t$), smoothing parameters set to $\alpha = 0.8$, $\beta = 0.2$, $\gamma = 0.1$.



- **Auto SARIMA:** Automatic selection of Seasonal ARIMA (SARIMA$(p,d,q)\times(P,D,Q)_m$) with a 7-day cycle ($m = 7$), parameters optimized automatically.
- **Manual SARIMA:** Manually defined SARIMA model with non-seasonal order $(1,1,1)$ and seasonal order $(1,1,1,7)$, capturing weekly patterns.
- **Linear Regression:** The duration is predicted using:

$$y_t = \beta_0 + \beta_1 \tau_t + \sum_{i=1}^{6} \beta_i D_i + \sum_{j=1}^{11} \beta_j M_j + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma^2)$$

Visualization

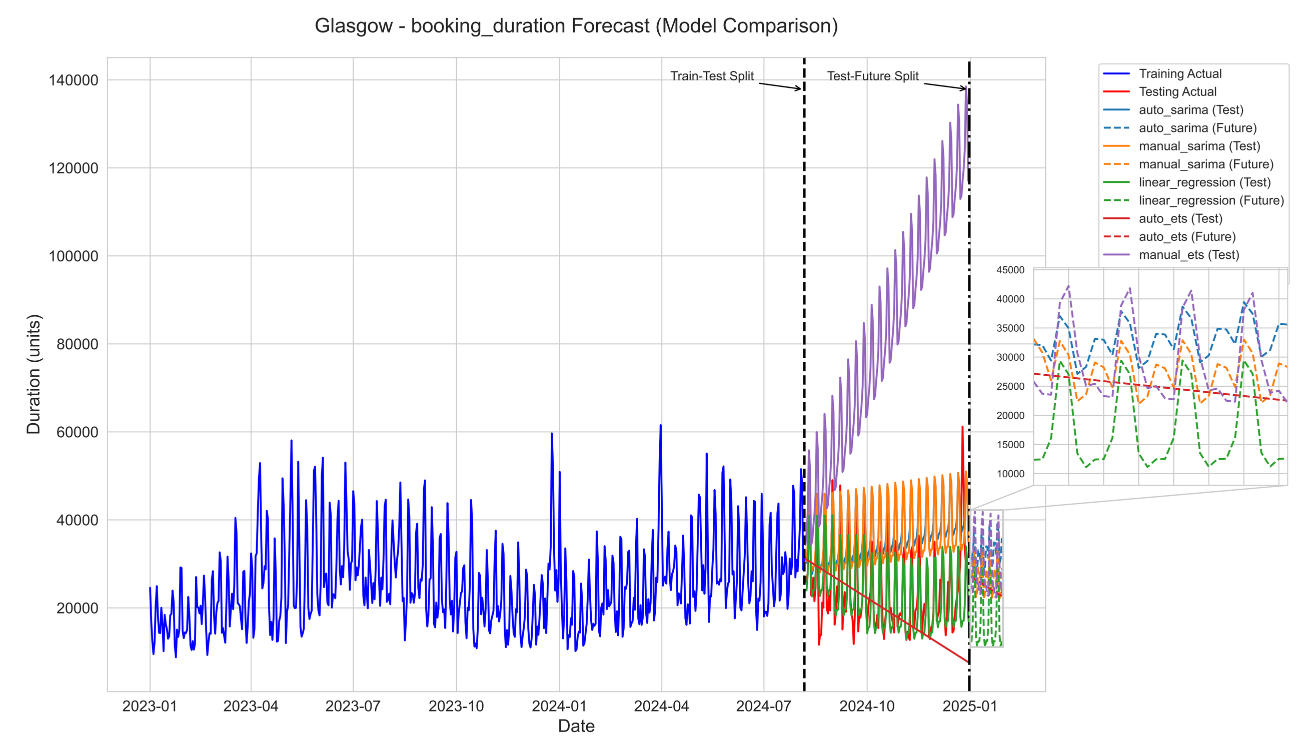


Figure 1: Multi-Models Duration Forecasting by Overall

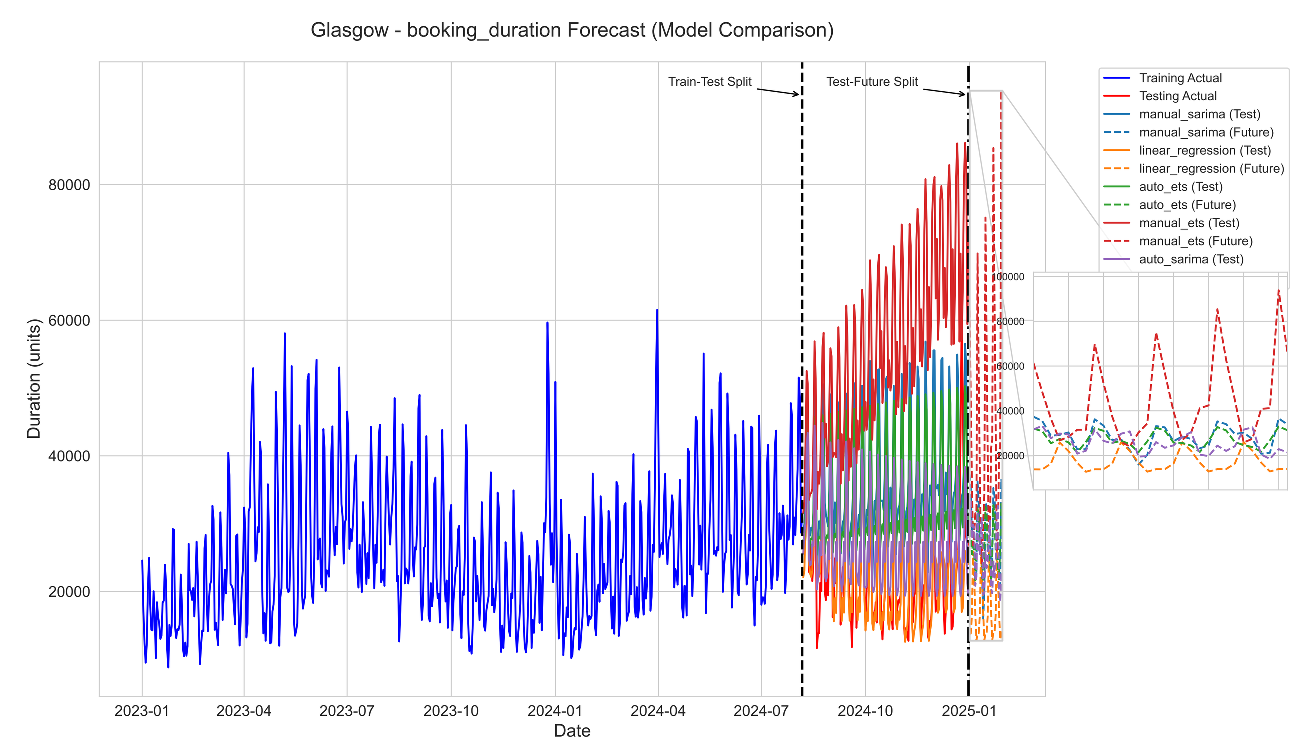


Figure 2: Multi-Models Duration Forecasting by Day of the Week

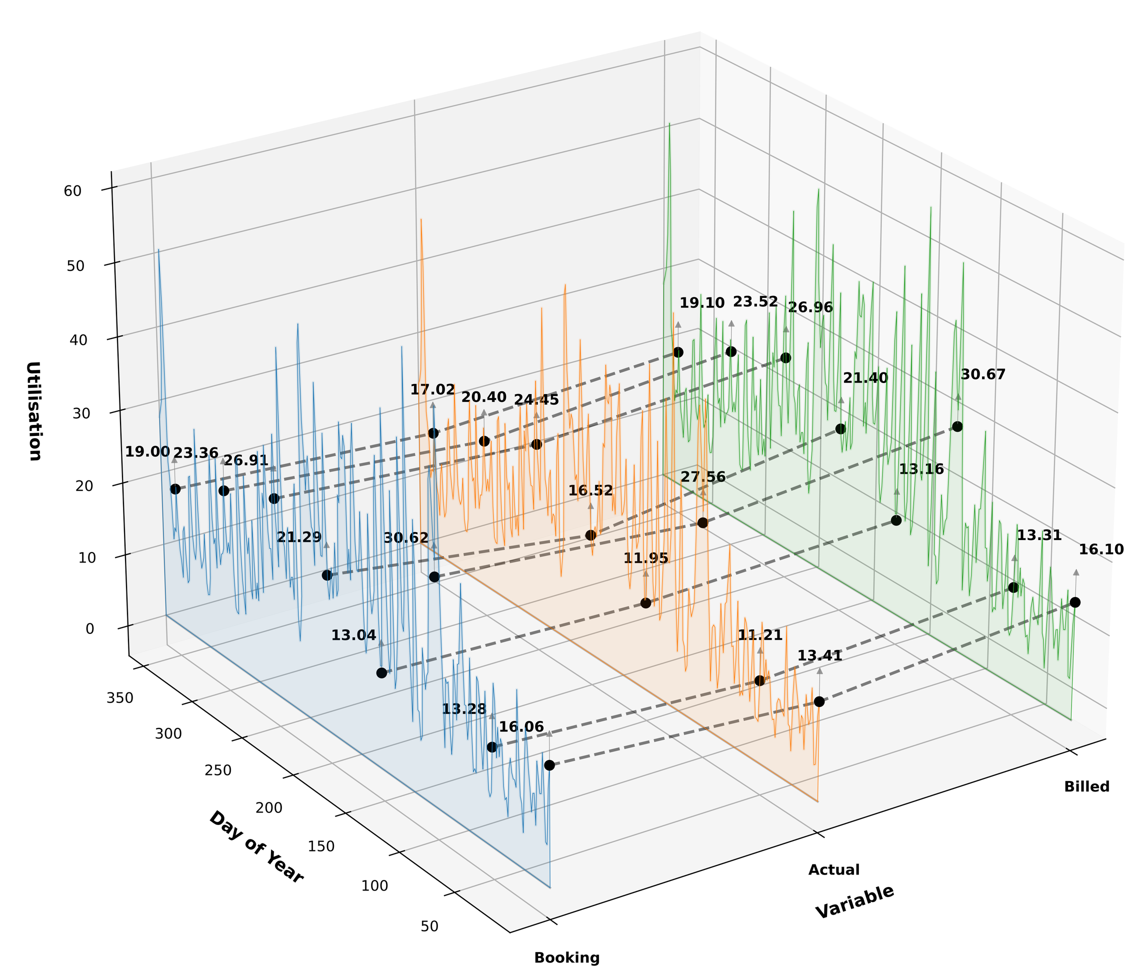


Figure 3: Vehicle Utilisation Visualisation (based in Glasgow)

Data Processing Methods

- Constructs city-level booking activity by distinguishing between planned and realized usage, capturing daily mobility demand more accurately.
- Applies proportional allocation and temporal segmentation to improve the precision of usage pattern analysis.
- Mitigates data irregularities through imputation and outlier detection to enhance analytical reliability.

Discussion

- **Forecasting Performance**: Linear Regression excels in long-term forecasting but is unstable for short-term predictions. Auto SARIMA performs best for short-term forecasting, while Auto ETS maintains balanced accuracy across both horizons.
- **Part A vs. Part B**: Short-term forecasts (Part B) have lower errors due to reduced cumulative effects. Auto SARIMA improves most in Part B, Linear Regression worsens, and Auto ETS remains the most stable across both.
- **Automated vs. Manual Models**: Manual ETS and Manual SARIMA show the highest errors, highlighting the superiority of automated models in ensuring accuracy and stability for time series forecasting.

Table 1: Error Metrics

Model	MAE	MSE	RMSE
Part A: Overall Error Metrics			
Auto ETS	9584.65	1.60e+08	12671.82
Auto SARIMA	13577.66	2.20e+08	14830.70
Linear Regression	4237.80	4.70e+07	6854.20
Manual ETS	58211.94	4.09e+09	63965.34
Manual SARIMA	12768.19	1.94e+08	13935.59
Part B: Error Metrics by Day of Week			
Auto ETS	1545.47	4.47e+06	1995.92
Auto SARIMA	1248.47	3.22e+06	1752.00
Linear Regression	1882.56	1.99e+07	2271.33
Manual ETS	2248.85	2.37e+07	2838.62
Manual SARIMA	1450.92	4.45e+06	2032.84

Conclusions

- Considering the seasonality and trends in real-world data, decomposition-based forecasting has greater advantages compared to direct forecasting.
- Spatiotemporal variation in demand underscores the need to account for time, location, and contextual factors in operational planning.
- Accurate forecasting enables more efficient fleet allocation, reducing idle capacity and improving service responsiveness during peak periods.

Acknowledgments

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