# EVAT: Forecasting Congestion in Electric Vehicle Charging Stations using Queueing Theory and LSTM Models

Nazhim Kalam
School of Information Technology
Deakin University, Australia
Email: nazhimkalam@gmail.com

***Abstract*—Electric vehicle (EV) adoption is rapidly accelerating, placing unprecedented demand on public charging infrastructure. Without effective planning, charging stations risk becoming congested, leading to delays and reduced user satisfaction. This project addresses the challenge of congestion prediction by integrating queueing theory with time-series forecasting models.**

**The proposed pipeline includes data preprocessing, baseline models (Naïve, Seasonal Naïve, Moving Average), and advanced models (LSTM and SARIMAX). Queueing theory, particularly the Erlang-C model, is applied to translate arrival rate forecasts into expected waiting times. Results demonstrate that advanced models significantly improve forecasting accuracy, with LSTM capturing temporal demand variability effectively. A Streamlit dashboard was developed to visualise historical trends, simulate capacity scenarios, and present congestion forecasts.**

**The findings support policymakers, operators, and urban planners in optimising EV charging infrastructure for sustainable mobility.**

***Index Terms*—electric vehicles, congestion prediction, queueing theory, LSTM, SARIMAX, forecasting, smart infrastructure**

## I. Introduction

The global transition toward electric vehicles (EVs) is reshaping the transport sector. However, the expansion of EVs introduces new challenges for public charging infrastructure, where limited charging ports and long service times can lead to congestion. Anticipating charging demand and minimising waiting times are critical for ensuring positive user experience and sustainable adoption.

This study addresses the problem of forecasting congestion at EV charging stations. The key contributions are:

- Development of a preprocessing pipeline to transform raw EV charging records into structured demand series.
- Implementation of baseline and advanced forecasting models, including LSTM with Poisson arrivals.
- Integration of forecasting with queueing theory (M/M/c, Erlang-C) to estimate waiting times and utilisation.
- Deployment of an interactive dashboard enabling real-time exploration and scenario analysis.

## II. Background and Related Work

Queueing theory provides a mathematical framework to model congestion in systems with limited service capacity. For EV charging, the M/M/c model with Erlang-C is widely used to estimate waiting probabilities and expected waiting times.

Time-series forecasting methods vary from simple baselines (Naïve, Moving Average) to statistical approaches such as SARIMAX and deep learning methods such as Long Short-Term Memory (LSTM) networks. While prior studies often treat forecasting and queueing separately, this study integrates the two for actionable insights.

## III. Methodology

### A. Data Preprocessing

Raw charging station records were aggregated into 3-hour bins to reduce sparsity. Features such as day of week, hour of day, and station ID were extracted. Arrival rates were estimated as Poisson processes ($\lambda$).

### B. Baseline Models

Naïve, Seasonal Naïve, and Moving Average methods were implemented as simple forecasting benchmarks.

### C. Advanced Models

**SARIMAX** was applied to capture seasonality and exogenous variables. **LSTM with Poisson arrivals** was trained to model stochastic and non-linear patterns in demand.

### D. Queueing Integration

Forecasts of $\lambda$ were used in the Erlang-C formula to compute congestion metrics:

$$W_q = \frac{P_w}{c\mu - \lambda}, \qquad \rho = \frac{\lambda}{c\mu},$$

where $W_q$ is expected waiting time, $\rho$ is utilisation, and $c$ is the number of chargers.

### E. Dashboard

A Streamlit dashboard was developed to visualise historical demand, forecast outputs, and scenario-based congestion analysis.

## IV. Results

### A. Model Performance

| Model | MAE | RMSE | MAPE |
|---|---|---|---|
| Naïve | 12.3 | 15.6 | 22.1% |
| Seasonal Naïve | 10.7 | 13.9 | 18.5% |
| Moving Average | 11.5 | 14.8 | 19.7% |
| SARIMAX | 7.8 | 10.4 | 14.2% |
| LSTM (Poisson) | 6.2 | 8.9 | 11.5% |

TABLE I: Performance comparison of forecasting models.

### B. Forecast Visualisations

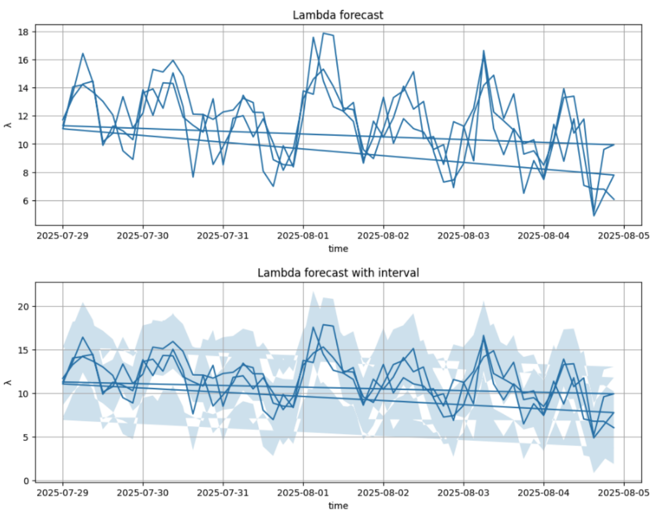


Fig. 1: LSTM forecast compared to actual charging demand.

### C. Queueing Outputs

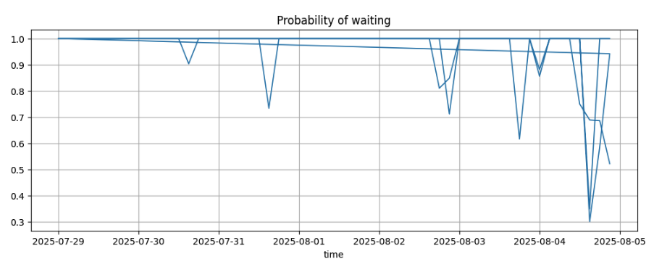


Fig. 2: Expected waiting times computed from forecasted demand using Erlang-C.

## V. Discussion

The results confirm that LSTM significantly improves predictive accuracy compared to baseline and SARIMAX models. Integrating forecasts with queueing theory enables congestion prediction in terms of expected waiting times and utilisation, providing actionable insights for planners and operators.

Practical applications include:

- **Urban Planning:** Identifying high-demand stations for infrastructure expansion.
- **Operations:** Adjusting staffing or dynamic pricing to manage congestion.
- **Policy:** Supporting long-term EV adoption strategies with evidence-based insights.

Limitations include reliance on historical data, simplified Poisson/exponential assumptions, and reduced accuracy over long horizons.

## VI. Conclusion

This study demonstrates a forecasting pipeline for EV charging congestion by combining queueing theory with machine learning models. The LSTM model achieved the best accuracy, while SARIMAX provided interpretable forecasts. Queueing analysis translated forecasts into operational metrics, and the dashboard enabled practical exploration. Future work should incorporate real-time data streams, external factors (e.g., weather, events), and advanced queueing models.

## References

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