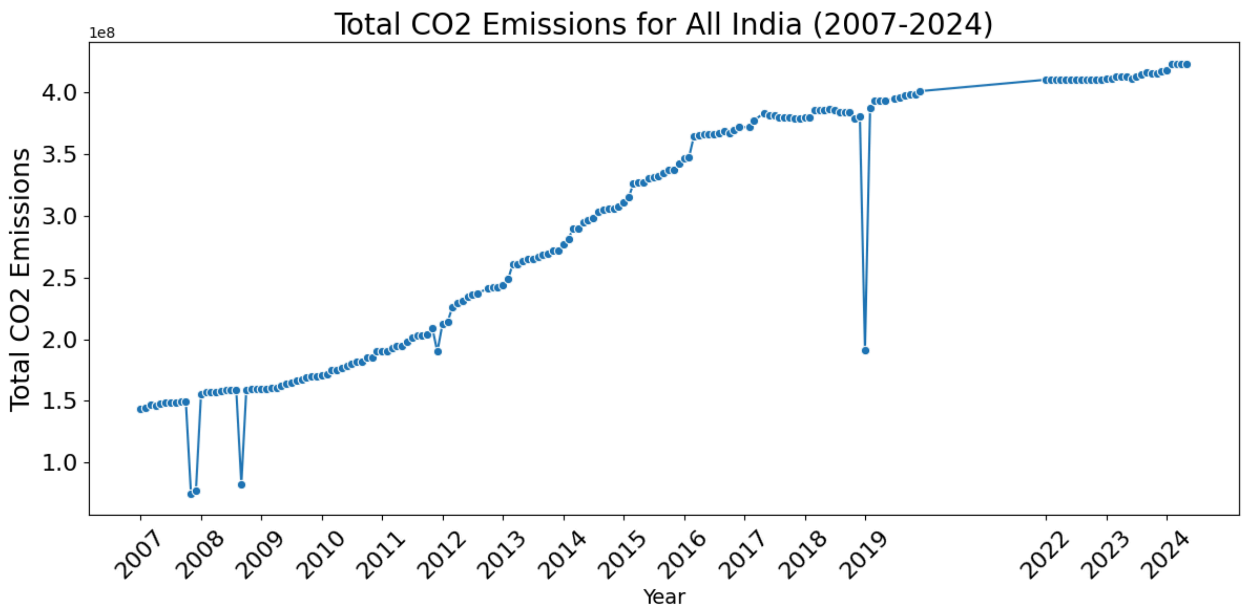
Results and Analysis of Carbon Emission Predictions and Vehicle Comparisons

5.1 Temporal Analysis of Vehicle CO_2 Emissions (2007-2024)



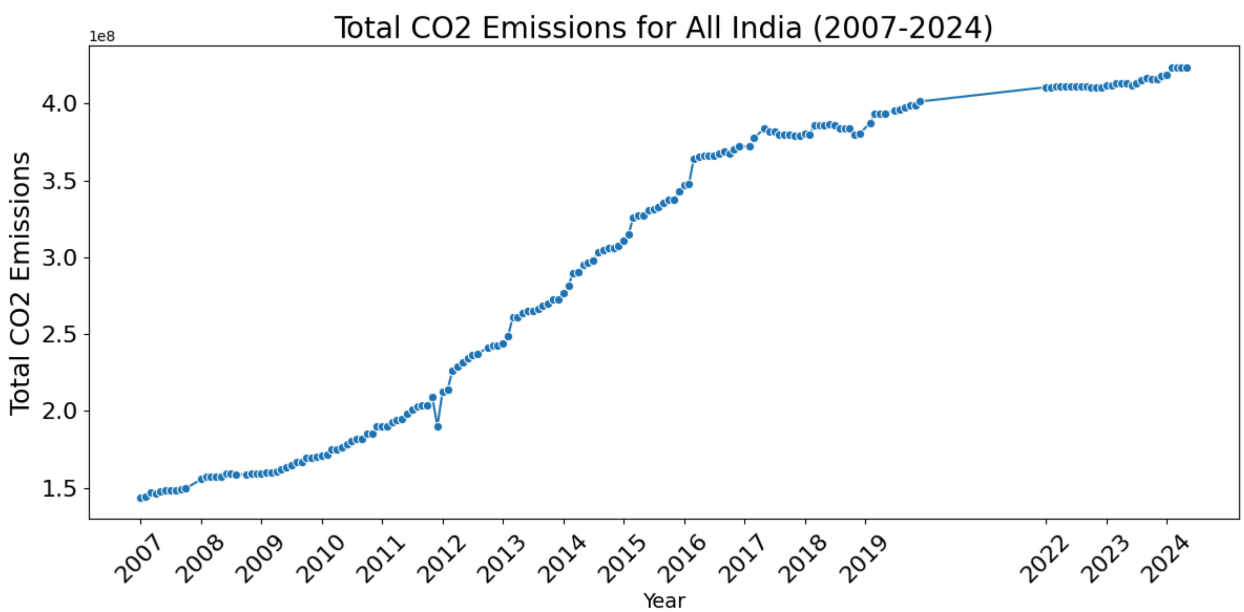


Fig.6 (a) Time series before outlier removal for the years 2007 - 2024 (b) Time series after outlier removal for the years 2007 - 2024

Our longitudinal analysis of India's CO_2 emissions and energy production from 2007 to 2024 reveals distinctive patterns in environmental impact and energy generation. The raw time series data exhibited a pronounced upward trajectory, with total CO_2 emissions escalating from 1.5×10^8 units (2007) to approximately 4.0×10^8 units (2024). Notable anomalies were observed in the form of downward spikes during 2008, 2009, and 2019, which were attributed to data collection inconsistencies rather than genuine emission reductions.

Post-outlier removal analysis unveiled three distinct growth phases:

1. Initial slow growth phase (2007-2012)
2. Rapid acceleration phase (2012-2018)
3. Moderate growth phase (2018-2024)

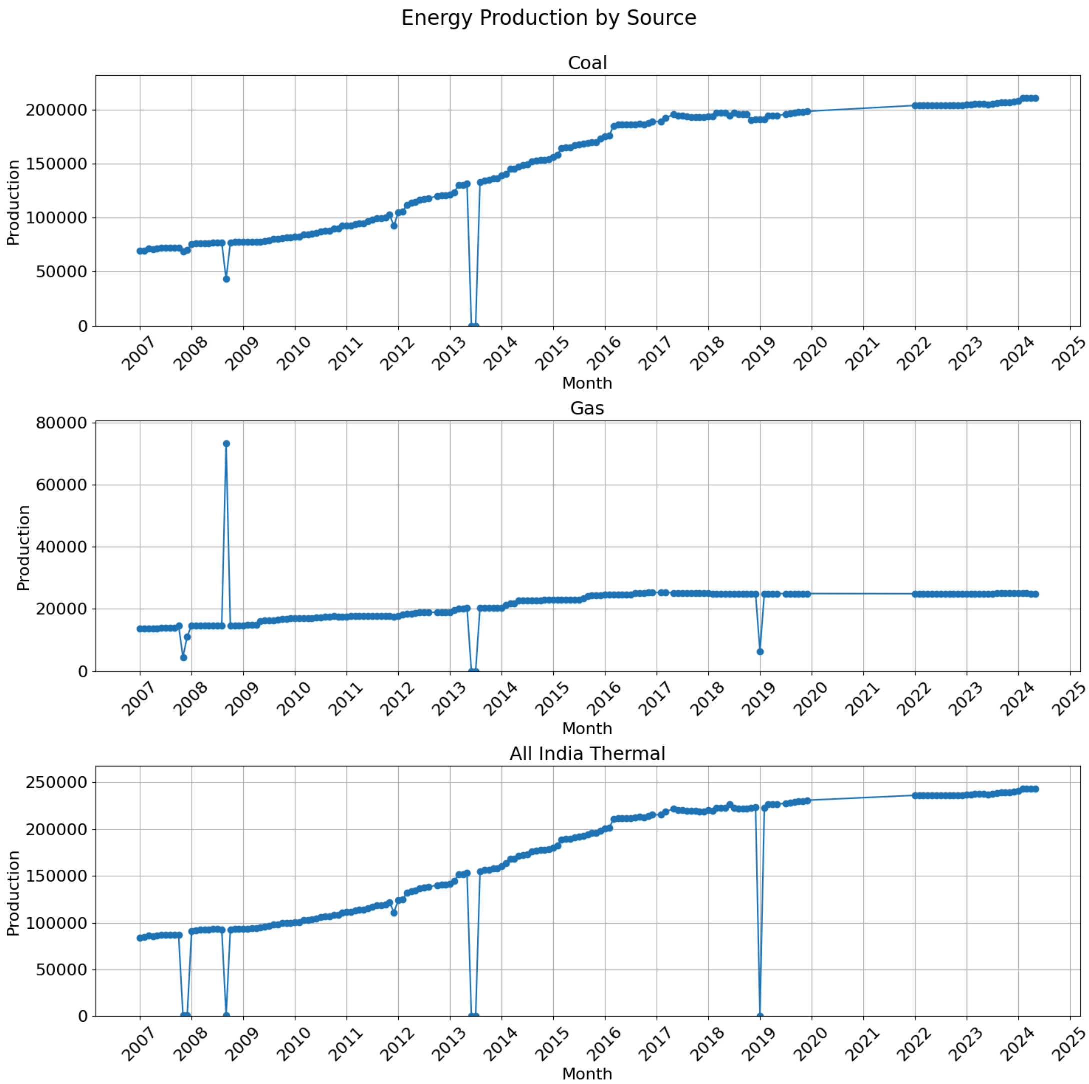


Fig.7 Energy productions by source for Coal, Gas and All India Thermal

The energy production analysis demonstrates coal's dominance in India's energy landscape, with production increasing from 70,000 units (2007) to approximately 200,000 units (2024). Gas production maintained relatively stable levels around 25,000 units, with an anomalous peak of 70,000 units in 2009. The overall thermal energy production patterns closely aligned with coal production trends, emphasizing coal's pivotal role in India's energy matrix.

5.2 Comparative Performance Analysis of CO_2 Emission Prediction Models

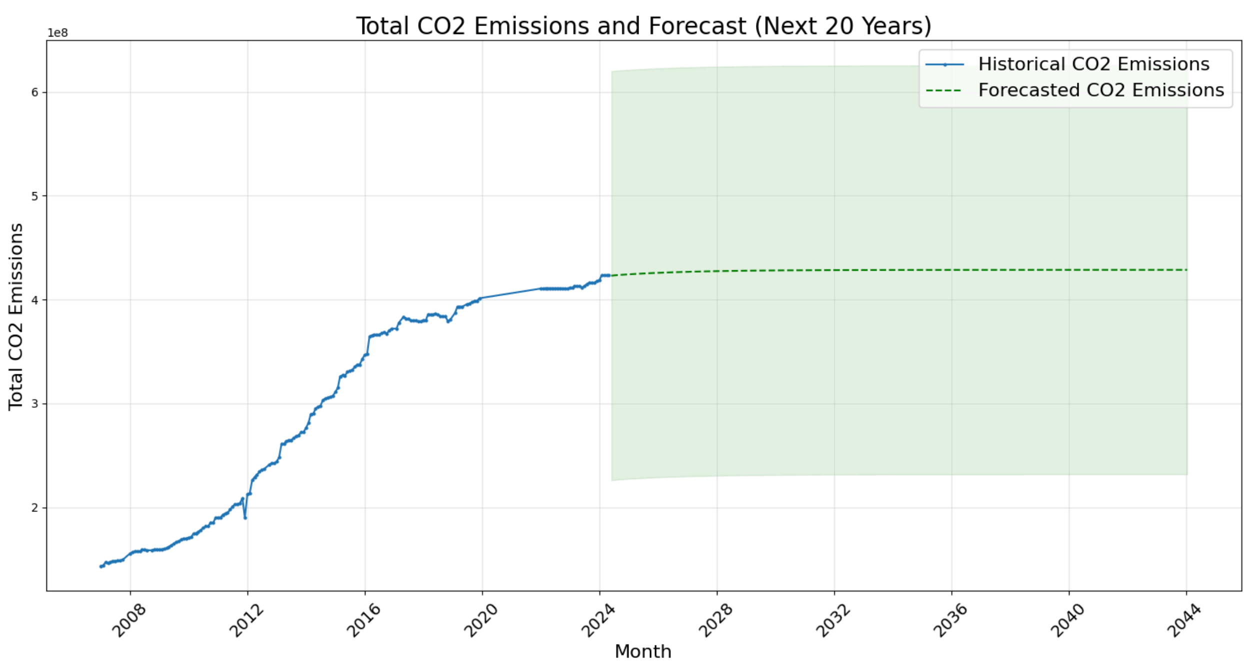
Our evaluation encompassed four distinct prediction models: Prophet, LSTM, SARIMA, and a Hybrid model (XGBoost+ARIMA). Performance assessment utilized Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics:

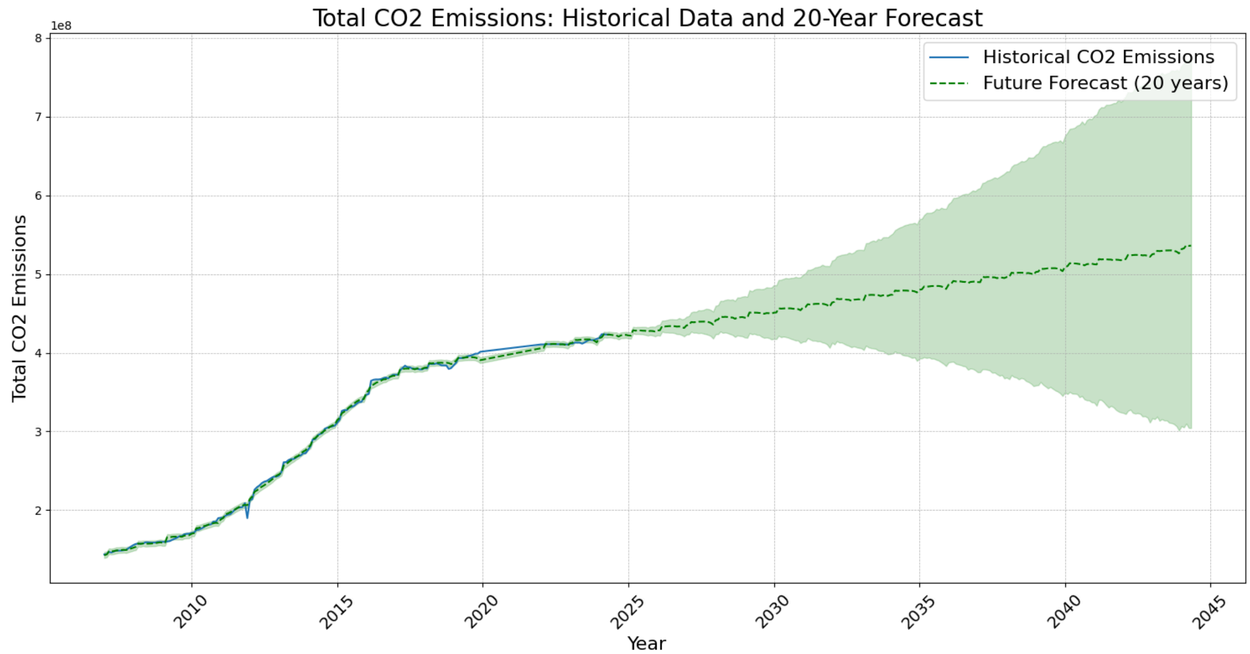
Model Type	**MAE**	**RMSE**
Prophet	0.68%	0.97%
LSTM	0.99%	1.30%
SARIMA	1.35%	5.03%
Hybrid (XGB+ARIMA)	1.66%	4.27%

The Prophet model demonstrated superior performance across both metrics, with the lowest MAE (0.68%) and RMSE (0.97%). LSTM showed comparable accuracy, particularly in avoiding significant prediction errors. However, SARIMA and the Hybrid model exhibited notably higher error rates, with SARIMA recording the highest RMSE at 5.03%.

5.3 Long-term Carbon Emission Projections (2025-2045)

Our analysis of CO_2 emissions trends combines historical data (2010-2025) with future projections (2025-2045). The historical data shows a marked increase between 2013-2015, followed by moderate growth, reaching approximately $4.2\text{-}4.3\times10^8$ units by 2025.





Total CO2 Emissions: Historical Data and 20-Year Forecast
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8
7
6
5
4
3
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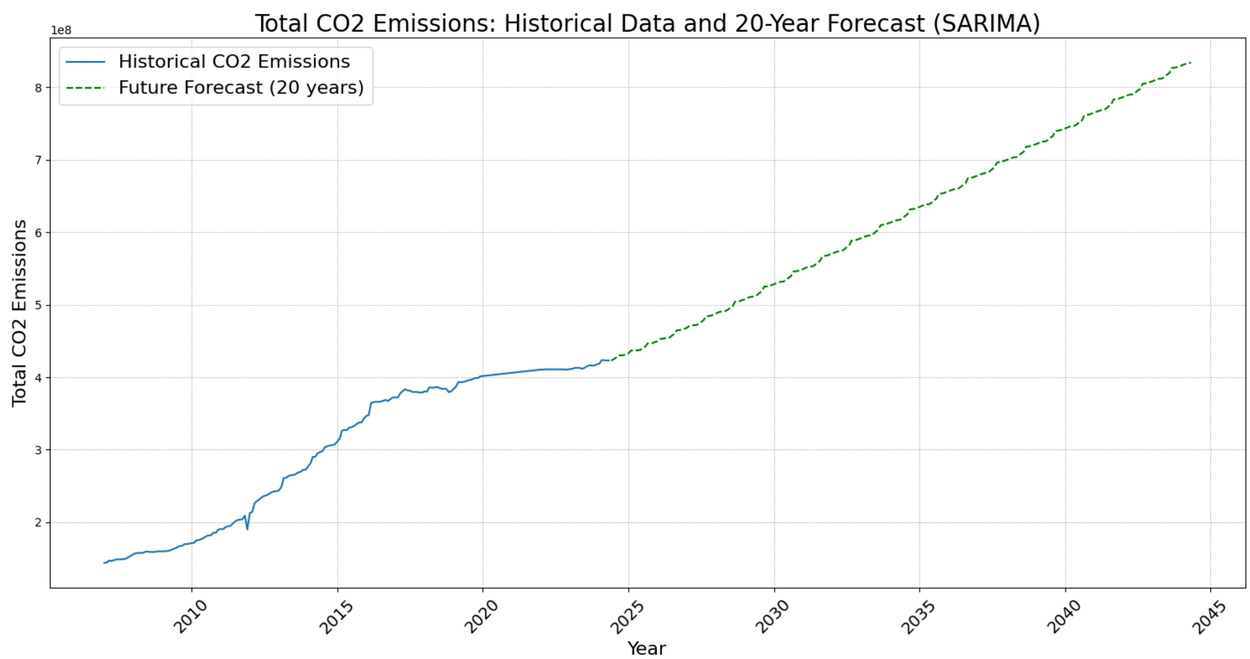
Total CO2 Emissions
Historical CO2 Emissions
Future Forecast (20 years)
2010
2015
2020
2025
2030
2035
2040
2045
Year



Total CO2 Emissions: Historical Data and 20-Year Forecast (SARIMA)
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Total CO2 Emissions
Historical CO2 Emissions
Future Forecast (20 years)
2010
2015
2020
2025
2030
2035
2040
2045
Year

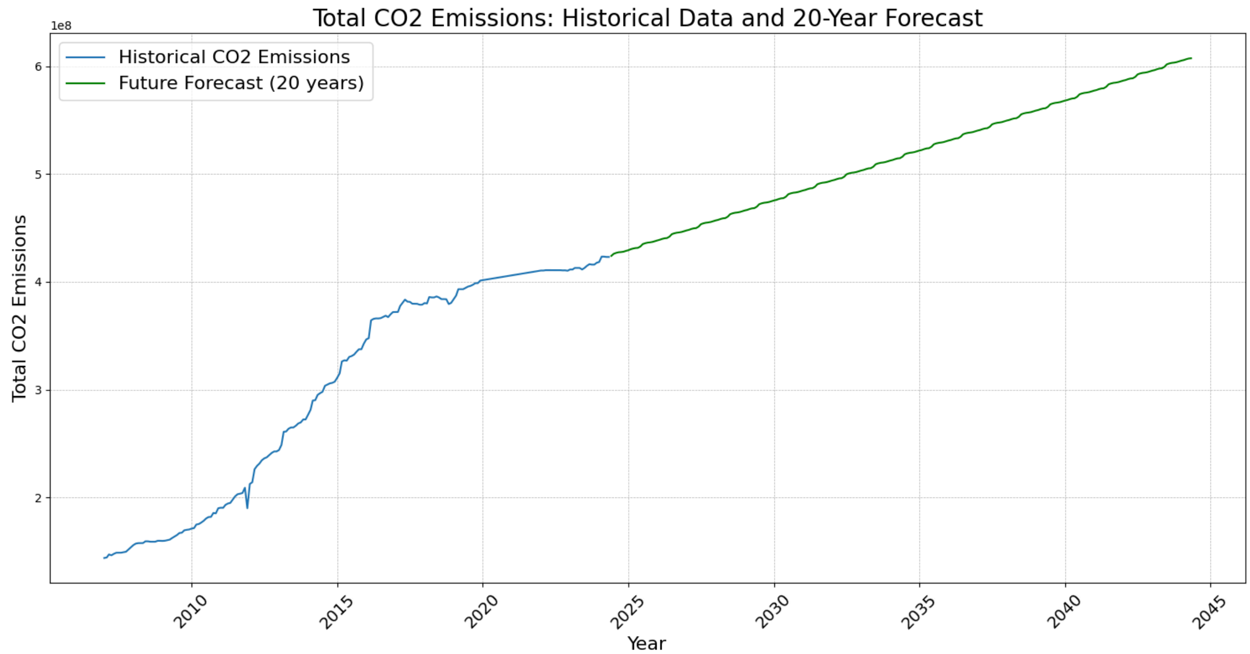

Fig.8 (a) LSTM-Based Long-Term Carbon Emission Projections (b) Prophet-Based Long-Term Carbon Emission Projections (c) SARIMA-Based Long-Term Carbon Emission Projections (d) Hybrid(XGboost+SARIMA)-Based Long-Term Carbon Emission Projections for the years 2025-2045

Model-specific projections revealed:

1. Prophet Model:
   - Most conservative and realistic forecast
   - Projects approximately 5.3×10^8 units by 2045
   - Features expanding confidence intervals reflecting increasing uncertainty
   - Superior performance metrics (MAE: 1.99 million, RMSE: 2.83 million)
2. SARIMA Model:
   - Aggressive linear projection reaching 8.5×10^8 units by 2045
   - Higher error metrics (MAE: 3.94 million, RMSE: 14.68 million)
   - Limited consideration of technological advancements and policy interventions
3. Hybrid Model:
   - Intermediate projection of 6×10^8 units by 2045
   - Linear growth pattern lacking nuanced behavior
   - Highest MAE (4.84 million) despite theoretical sophistication

5.4 Extended Temporal Forecast Analysis (2025-2075)

The Prophet model's performance across different temporal horizons showed:

Forecast Horizon	MAE		RMSE
20-Year	0.68%		0.97%
50-Year	2.03%		2.29%

Table.4 Evaluation Metrics of Prophet Model Performance Across Long-Term Temporal Horizons

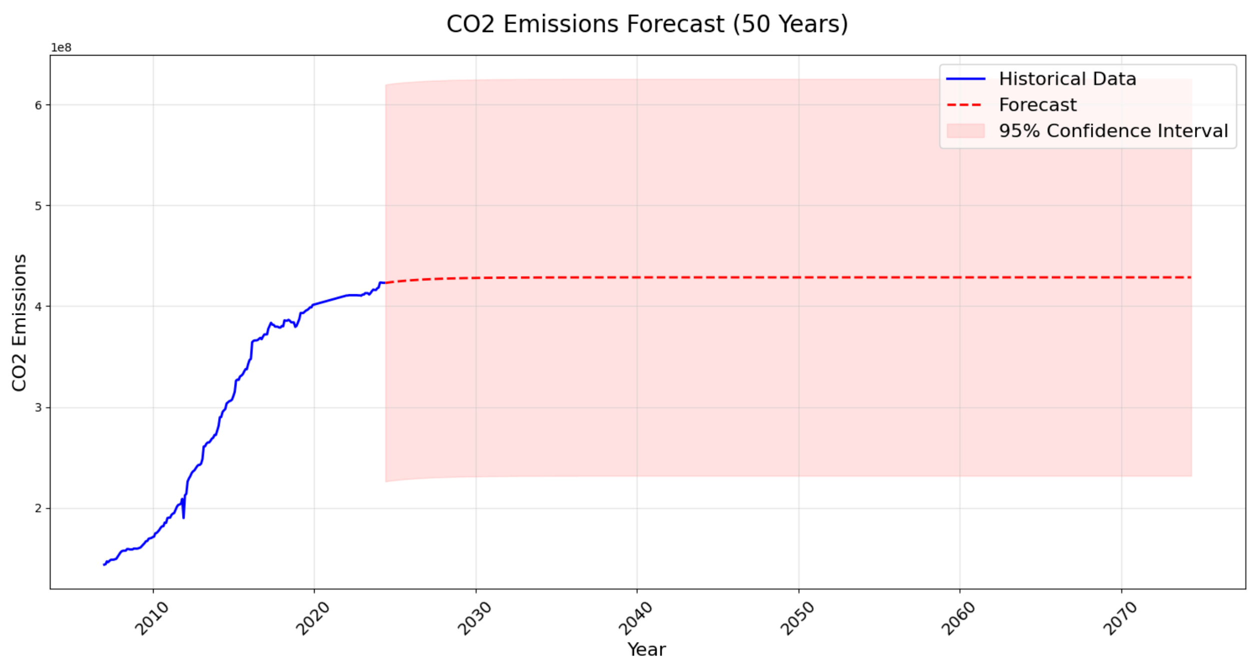

Fig.9 Prophet-Based Long-Term Carbon Emission Projections (2025-2075)

Long-term projections indicate a continuing upward trend with decreasing growth rate. The model projects emissions reaching approximately 0.7×10^9 units by 2070, with significantly expanding confidence intervals reflecting increased uncertainty in longer-term predictions.

5.5 Comparative Analysis of Carbon Emissions Between Electric and Conventional Vehicles

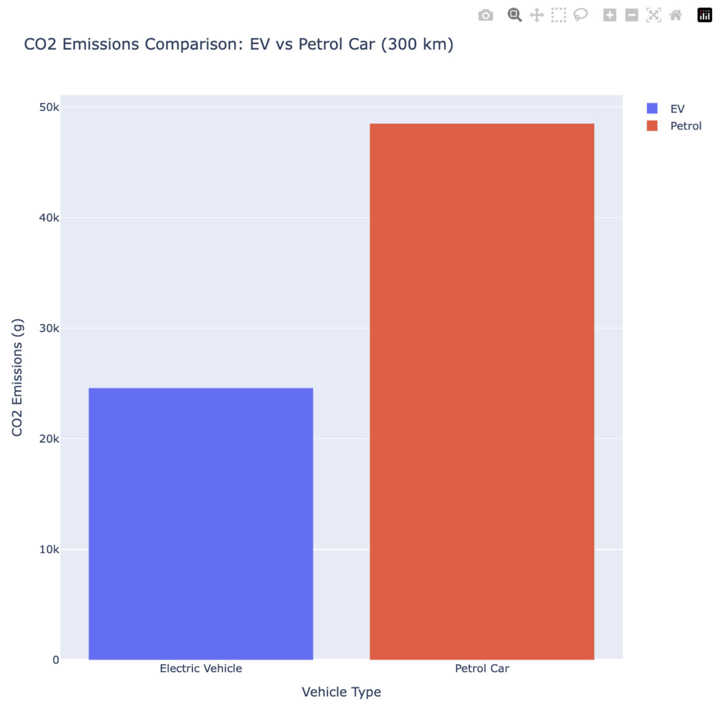

Fig.11 CO2 Emissions Comparison Between Electric and Petrol Vehicles for 300km

The comparative analysis of CO_2 emissions between electric vehicles (EVs) and conventional petrol cars over a 300-kilometer distance reveals significant disparities in environmental impact. The data visualization demonstrates that for this specific distance, EVs generate approximately 24,000 grams (24 kg) of CO_2, while petrol vehicles produce approximately 48,000 grams (48 kg) of CO_2. This represents a consistent 2:1 ratio in emissions output, with conventional petrol vehicles producing twice the carbon emissions of their electric counterparts. The substantial difference of 24 kg in CO_2 emissions for a relatively short journey of 300 kilometers underscores the environmental advantages of electric vehicles in urban and suburban transportation scenarios. This finding aligns with broader environmental impact assessments and supports the argument for increased adoption of electric vehicles as a strategy for reducing transportation-related carbon emissions. The clear linear relationship between vehicle type and emissions output provides a reliable basis for extrapolating environmental impact across various journey distances, offering valuable insights for both policy makers and consumers in transportation planning and vehicle selection.

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