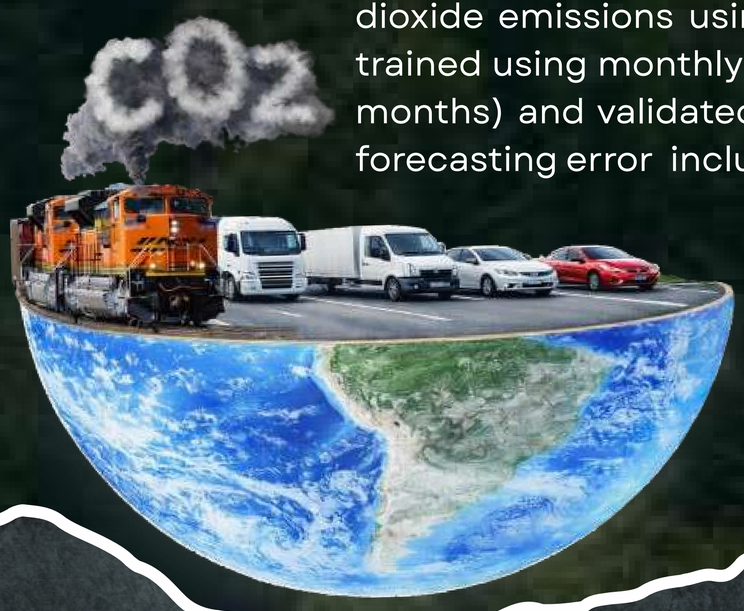
FORECASTING MODEL FOR CO_2 EMISSIONS IN THE TRANSPORTATION SECTOR

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Abstract

To achieve Carbon Neutrality by 2050, Thailand requires precise insights into the transport sector a major and complex contributor to national emissions. This study develops and evaluates eight forecasting models for Carbon dioxide emissions using time series data: SARIMA, RNN, LSTM, XGBoost, LightGBM and Transformer. The models were trained using monthly Carbon dioxide emission data from the transport sector from January 2014 to December 2024 (132 months) and validated against a test set from January 2025 to December 2025 (12 months). The evaluation criteria for forecasting error included the Mean Absolute Percentage Error (MAPE).



Introduction

Carbon dioxide emissions are a key contributor to climate change, and the transport sector is one of the major emission sources due to its dependence on fossil fuels and growing Consequently, decarbonizing this sector is imperative to achieving global net-zero targets and mitigating the long-term impacts of global warming.

Objectives

1. To analyze the trend and patterns of Carbon dioxide emissions in Thailand's transport sector using monthly time series data from January 2014 to December 2024.
2. To develop and implement six forecasting models for example; SARIMA, RNN, LSTM, XGBoost, LightGBM and Transformer for predicting Carbon dioxide emissions in the transport sector.

Methodology



Model Architecture

SARIMA

$$\left(1-\sum_{i=1}^{p}\phi_i B^i\right)\left(1-\sum_{k=1}^{P}\Phi_k B^{kS}\right)(1-B)^d(1-B^S)^D Y_t = \left(1-\sum_{j=1}^{q}\theta_j B^j\right)\left(1-\sum_{l=1}^{Q}\Theta_l B^{lS}\right)\epsilon_t$$

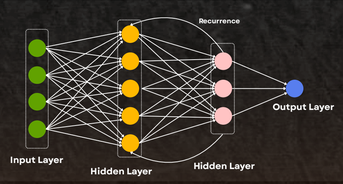
LightGBM



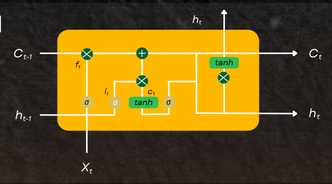
XGBoost



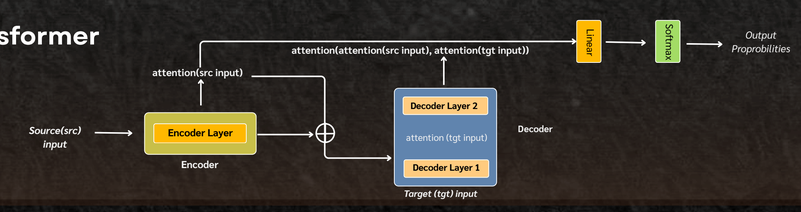
RNN



LSTM



Transformer



Evaluation Criteria

Mean Absolute Percentage Error

$$MAPE\,(\%) = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100$$

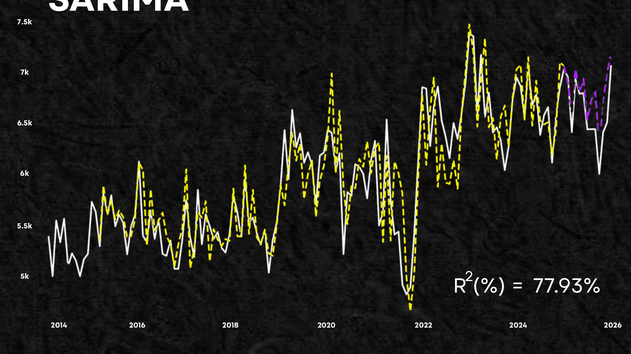
R-Squared

$$R^2\,(\%) = \left(1 - \frac{\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2}{\sum_{t=1}^{n}\left(Y_t - Y_t\right)^2}\right) \times 100$$

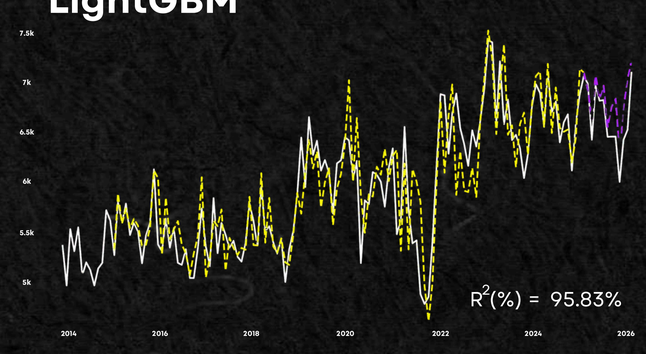
Experimental Result

The results show that **RNN is the most effective model** for Carbon dioxide emission forecasting, with the lowest MAPE in the training set of 1.18% and d MAPE in the test set of 1.57% . The R-Squared value is 92.15%.

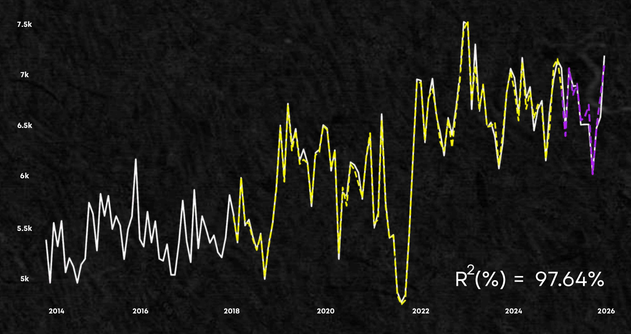
SARIMA



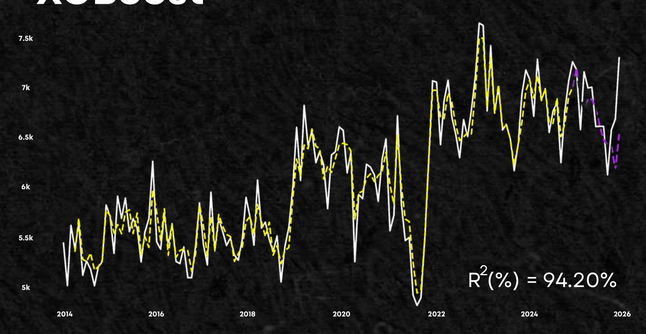
LightGBM



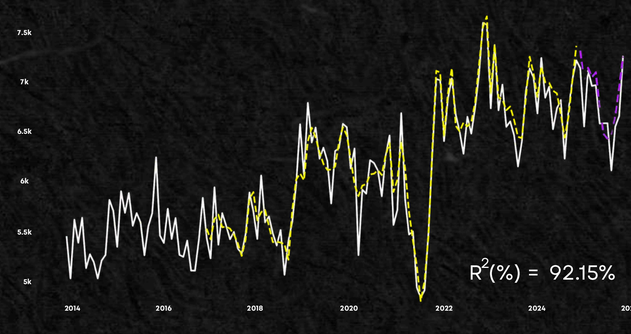
RNN



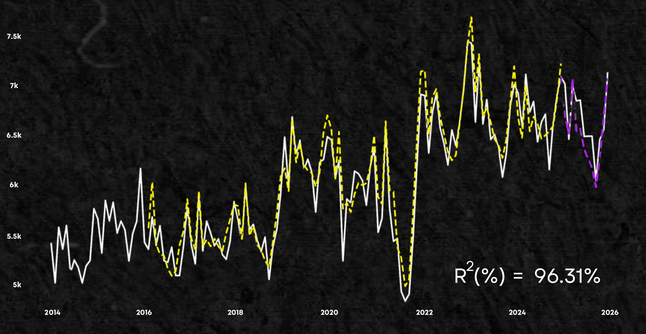
XGBoost



LSTM

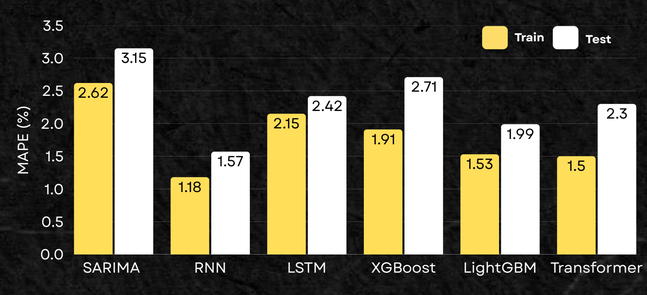


Transformer



CONCLUSION & DISCUSSION

The study found that the Recurrent Neural Network (RNN) model is the most effective for forecasting Carbon dioxide emissions in Thailand's transport sector, yielding the lowest MAPE for training 1.18% and testing 1.57%, along with an R^2(%) of 92.15%. The RNN's structure handles non-linear data significantly better than traditional statistical models (SARIMA), ensemble machine learning, and other deep learning models. These findings strongly align with Thananya Janhuaton et al. (2024) and Xavier Demeulenaere (2021), highlighting that neural networks are highly suitable for managing complex and volatile Carbon dioxide data.



This research supports Sustainable **Development Goal 7** (Affordable and Clean Energy) and **Goal 11** (Sustainable cities and communities) of the United Nations by providing analytical tools for sustainable environmental policy planning.

References

[1] Demeulenaere, X. (2021). Carbon Dioxide emissions of new UK passenger car registrations–Assessing technical and market evolutions in the past decade (2010-2019). Available at SSRN 4109169.

[2] Janhuaton, T., Ratanavaraha, V., & Jomnonkwao, S. (2024). Forecasting Thailand's transportation Carbon Dioxide emissions: A comparison among artificial intelligent models. Forecasting, 6(2), 462-484.