CO_2 Factor Forecasting – Report

1. Approach

The goal of this project was to forecast the CO_2 emission factor (gCO_2/kWh) for the next 7 days (hourly resolution), using historical renewable energy production and weather data as features.

Steps Taken:
1. Data Preparation:
- Combined 4 years of hourly data (2021–2024) including renewable generation (solar, wind, biomass, electricity volume) and weather variables (radiation, temperature, wind speed, sunshine, precipitation).
- Engineered time-based features (hour_sin, hour_cos, month, day_of_week) to capture daily and seasonal patterns.
- Removed redundant or highly correlated variables (capacity columns).

2. Feature Selection:
- Applied stepwise regression and correlation analysis to retain the 12 most relevant predictors

3. Modeling Approach:
- Trained multiple ML models: OLS, Ridge, Lasso, Random Forest, XGBoost (untuned and tuned), LightGBM, KNN, and MLP Neural Network.
- Used 80/20 train-test split and 5-fold cross-validation for evaluation.
- Hyperparameter tuning for XGBoost was performed using GridSearchCV.

2. Assumptions

- Weather and renewable generation strongly influence CO_2 factor, and past patterns are reliable predictors of future trends.
- Data from trusted sources (electricity and weather datasets) are accurate and free of outlier-related errors.
- Stationarity is not strictly required since tree-based models (XGBoost, RF) can handle trends and seasonality effectively.

3. Results

The following models were compared using metrics such as RMSE, MAE, and R^2 for both train and test sets. Cross-validation (CV RMSE) was also computed to ensure generalization performance.

Model	**RMSE (train)**	**MAE (train)**	**R^2 (train)**	**MAE (test)**	**R^2 (test)**	**CV RMSE (mean)**
OLS (Linear Regression)	0.0269	0.0210	0.9209	0.0256	0.9108	0.0305
Ridge	0.0269	0.0210	0.9209	0.0256	0.9108	0.0305
Lasso	0.0271	0.0212	0.9194	0.0263	0.9032	0.0310
Random Forest	0.0050	0.0036	0.9973	0.0149	0.9705	0.0229
XGBoost (untuned)	**0.0124**	**0.0092**	**0.9830**	**0.0127**	**0.9784**	**0.0214**
XGBoost (tuned)	**0.0133**	**0.0099**	**0.9806**	**0.0118**	**0.9816**	**0.0208**
LightGBM	0.0106	0.0079	0.9877	0.0125	0.9792	0.0212
KNN	0.0155	0.0115	0.9735	0.0142	0.9725	0.0224
MLP Neural Network	0.0208	0.0161	0.9524	0.0179	0.9524	0.0239

The best performing model is the tuned XGBoost, as it achieves the highest R^2 and lowest RMSE and MAE on the test set.

RMSE (train) and RMSE (test) are slightly different, showing that there are no overfitting issues.

The actual and predicted CO_2 factor values overlap closely, indicating that the tuned XGBoost model captures the temporal patterns effectively with minimal error. (Figure 1)

The residuals are centered around zero and approximately normally distributed, showing that the model's predictions are unbiased and consistent. (Figure 2)

Figure 3 shows that the most important features are onshore_wind_volume, solar_volume, biomass_volume.

Figure 1: Actual vs Predicted CO_2 Factor (Tuned XGBoost).

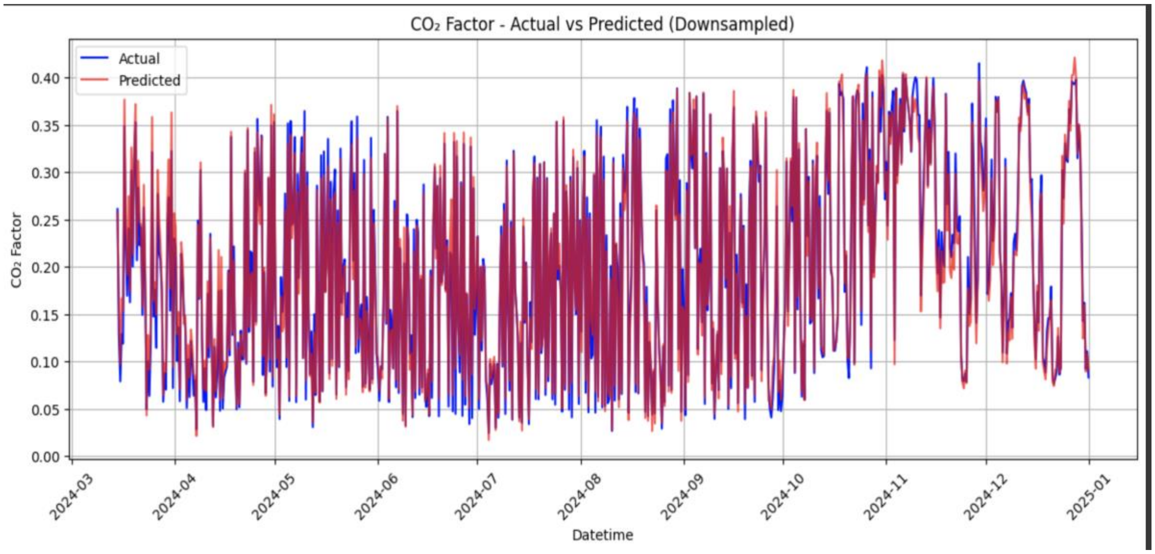


Figure 2: Residuals Distribution

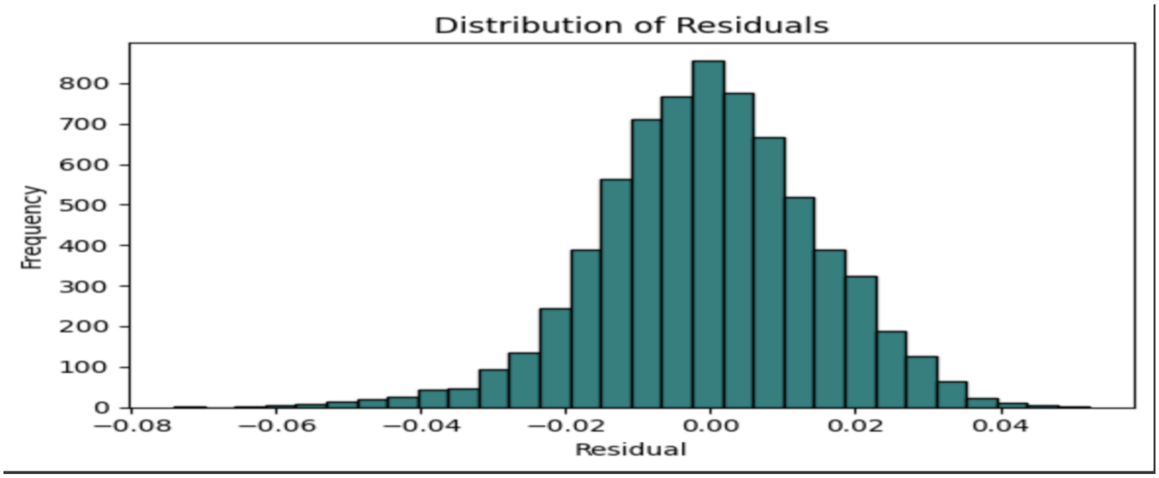
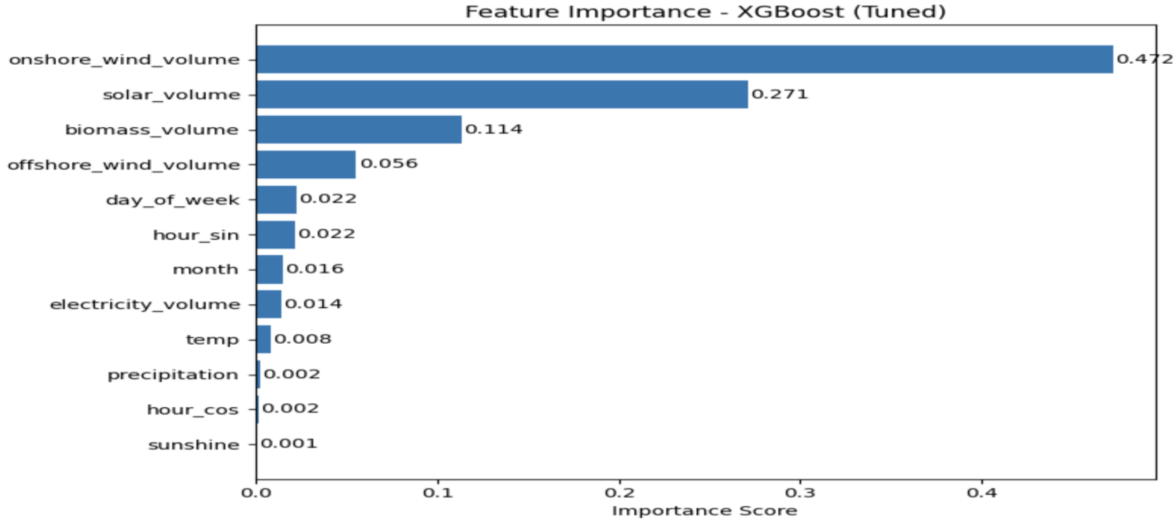


Figure 3: Feature Importance (Tuned XGBoost)


Feature Importance - XGBoost (Tuned)
onshore_wind_volume
solar_volume
biomass_volume
offshore_wind_volume
day_of_week
hour_sin
month
electricity_volume
temp
precipitation
hour_cos
sunshine
Importance Score