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ARTICLE

Machine Learning for Urban Traffic Carbon Emission Prediction in Norway: A Case Study of Bergen

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ABSTRACT

Norway's goal of achieving carbon neutrality by 2050 requires precise monitoring and prediction of urban traffic emissions, a major contributor to national greenhouse gas output. This study applies three machine learning models—Random Forest Regressor (RFR), Gradient Boosting Regressor (GBR), and Artificial Neural Network (ANN)—to predict hourly urban traffic carbon emissions in Bergen, using a 2022–2023 dataset integrating traffic flow, vehicle type (electric vs. conventional), meteorological conditions, and road network characteristics. Results show GBR outperforms other models: it achieves a Mean Absolute Error (MAE) of 0.28 kgCO/h, Root Mean Squared Error (RMSE) of 0.39 kgCO/h, and Mean Absolute Percentage Error (MAPE) of 5.23%. Compared to RFR and ANN, GBR reduces MAE by 18.8% and 24.3%, respectively. The model effectively captures emission variations from Norway's high electric vehicle (EV) penetration (80% of new car sales in 2023) and provides actionable insights for Bergen's traffic emission reduction strategies.

Keywords: Urban traffic emissions; Carbon neutrality; Machine learning; Norway; Electric vehicles; Gradient Boosting Regressor; Bergen

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1. Introduction

1.1 Research Background

Norway leads Europe in EV adoption, with EVs accounting for 23% of all registered passenger cars in 2023—far exceeding the EU average of 3%. This shift has significantly reduced urban traffic emissions, but challenges remain: uneven EV penetration across city zones (e.g., higher EV rates in suburban vs. central areas), variable traffic flow (peak-hour congestion increases conventional vehicle emissions), and meteorological impacts (cold temperatures reduce EV battery efficiency, increasing indirect emissions from grid electricity). Bergen, Norway's second-largest city, faces unique emission challenges due to its hilly terrain (increasing fuel consumption for conventional vehicles) and narrow road networks (frequent congestion in the city center).

Accurate traffic emission prediction is critical for evaluating the effectiveness of EV incentives, congestion pricing, and public transportation improvements. Traditional emission models (e.g., COPERT, MOVES) rely on static emission factors and fail to capture real-time variations from EV integration and dynamic traffic conditions. Machine learning models, by contrast, can learn from multi-dimensional real-time data to predict emissions with higher precision—yet few studies have focused on Norway's EV-dominant traffic context.

1.2 Research Significance

This study contributes to both academic and practical domains:

Academic Contribution: It fills the gap in machine learning-based emission prediction for high-EV-adoption cities, providing a framework that integrates EV-specific features (e.g., battery state of charge, charging station density) into prediction models.

Practical Contribution: The results support Bergen's "Zero Emission City 2039" strategy by enabling targeted emission reduction measures—for example, predicting high-emission zones during cold weather to adjust EV charging infrastructure placement or public transport frequencies.

1.3 Literature Review

Recent studies have explored machine learning for traffic emission prediction, but few address Norway's context. Hansen et al. (2022) used RFR to predict emissions in Oslo, achieving a MAPE of 6.8%, but the model did not distinguish between EV and conventional vehicle emissions. Lunde et al. (2023) applied ANN to predict EV-related indirect emissions (from grid electricity) in Trondheim, but the model ignored conventional vehicle contributions.

GBR has shown promise in emission prediction for mixed vehicle fleets. Andersen et al. (2022) used GBR to predict emissions in Copenhagen, achieving a MAPE of 5.9%, but the study's low EV penetration (5% of cars) limits its applicability to Norway. RFR, while robust to outliers, struggles with non-linear relationships between EV battery efficiency and temperature—critical in Norway's cold climate. ANN, though capable of modeling complex interactions, requires large datasets and is prone to overfitting with limited samples.

1.4 Research Outline

The paper is structured as follows: Section 2 describes the dataset, including data sources (traffic, vehicle, meteorological) and preprocessing steps. Section 3 introduces the three machine learning models (RFR, GBR, ANN) and their adaptation to Bergen's traffic emission context. Section 4 presents experimental design, results, and detailed analysis. Section 5 concludes the study and proposes future research directions aligned with Norway's carbon neutrality goals.

2. Data Collection and Preprocessing

2.1 Study Area: Bergen

Bergen (60.39°N, 5.32°E) has a population of 285,911 and a traffic network spanning 1,200 km of roads. Key traffic characteristics include:

Vehicle Fleet: 21% EVs (2023), 58% conventional gasoline vehicles, 21% conventional diesel vehicles.

Road Network: 30% of roads are in hilly zones (slopes > 10%), 40% in flat central zones, 30% in suburban residential zones.

Emission Hotspots: City center (Kongens gate), port access roads (Bergen Havn), and commuter corridors (E39 highway) account for 65% of total traffic emissions.

The study focuses on 20 key road segments across Bergen's three zone types (hilly, central, suburban) to capture spatial emission variations.

2.2 Data Sources and Features

Data was collected from four primary sources between January 2022 and December 2023 (24 months), with a temporal resolution of 1 hour (total 17,520 samples per road segment):

Traffic Flow and Vehicle Type Data: From Bergen Municipal Transport Authority's automated traffic counters and license plate recognition (LPR) systems, including hourly counts of EVs, conventional gasoline vehicles, and conventional diesel vehicles per road segment.

Emission Data: From mobile emission sensors (deployed on 50 public transport buses) measuring real-time CO_2 emissions ($kgCO_2/h$) per road segment.

Meteorological Data: From MET Norway's Bergen weather station, including hourly temperature (°C), wind speed (m/s), and precipitation (mm).

Road and EV Infrastructure Data: From Bergen's municipal database, including road slope (%), number of lanes, and EV charging station density (stations/km) within 1 km of each road segment.

A total of 13 features were selected for prediction, categorized in Table 1:

Feature Category	Feature Name	Description
Traffic Features	EV count	Continuous: Number of EVs per hour on the road segment
	Gasoline vehicle count	Continuous: Number of conventional gasoline vehicles per hour
	Diesel vehicle count	Continuous: Number of conventional diesel vehicles per hour
	Average speed	Continuous: Average vehicle speed (km/h) on the road segment
Meteorological Features	Hourly temperature	Continuous: °C (range: -12°C to 22°C)
	Wind speed	Continuous: m/s (range: 0–18 m/s)
	Precipitation	Continuous: mm/h (range: 0–8 mm/h)
Road Features	Road slope	Continuous: % (range: -5% to 15%, negative for downhill)
	Number of lanes	Categorical: 1, 2, 3+
EV Infrastructure Features	Charging station density	Continuous: Number of EV charging stations per km within 1 km of the segment
Temporal Features	Time-of-day	Categorical: 00:00–06:00 (night), 06:00–12:00 (morning), 12:00–18:00 (afternoon), 18:00–24:00 (evening)
	Day-of-week	Binary: 1 (workday), 0 (weekend/holiday)
	Month	Categorical: 1 (Jan)–12 (Dec)

2.3 Data Preprocessing

To ensure model accuracy, the following steps were applied:

Missing Value Handling: Missing data (2.7% of total samples) included sensor malfunctions (emission sensors offline during heavy rain) and LPR system gaps. Missing values were imputed as follows:

◦Traffic and emission data: Mean value of the same hour, day-of-week, and month in the previous four weeks.

◦Meteorological data: Linear interpolation between adjacent hourly measurements.

Outlier Detection: Outliers (1.8% of total samples) were identified using the Z-score method (|Z| > 3) and were caused by extreme events (e.g., a 50% traffic surge during a concert at Bergenhus Fortress). Outliers were replaced with the median value of the surrounding 4 hours to preserve temporal trends.

Categorical Feature Encoding: Low-cardinality features (e.g., number of lanes, time-of-day) were encoded using one-hot encoding; high-cardinality features (e.g., month) were encoded using target encoding to avoid dimensionality inflation.

Feature Scaling: Continuous features (e.g., temperature, vehicle counts) were scaled to [0,1] using min-max scaling. This was critical for ANN, which is sensitive to feature magnitude differences.

The preprocessed dataset (20 road segments × 17,520 samples = 350,400 total samples) was split into training (70%), validation (15%), and test (15%) sets using time-based splitting: training (Jan 2022–Jun 2023), validation (Jul 2023–Sep 2023), test (Oct 2023–Dec 2023).

3. Machine Learning Models for Emission Prediction

3.1 Random Forest Regressor (RFR)

RFR is an ensemble model that constructs multiple decision trees and outputs the average prediction of all trees. It is robust to overfitting and handles non-linear relationships, making it suitable for emission prediction—especially for capturing interactions between vehicle counts and road slope.

In Bergen's context, RFR works by:

Generating bootstrap samples from the training data to build diverse trees.

At each tree split, randomly selecting a subset of features (e.g., EV count, road slope) to reduce tree correlation.

Averaging predictions across trees to minimize variance.

Key hyperparameters tuned for RFR:

Number of trees: 100–1000 (optimal: 300) – balancing accuracy and computational cost.

Maximum tree depth: 5–20 (optimal: 12) – preventing overfitting by limiting tree complexity.

Min samples per leaf: 1–20 (optimal: 4) – ensuring reliable leaf node predictions.

3.2 Gradient Boosting Regressor (GBR)

GBR builds trees sequentially, with each new tree correcting the errors of the previous ensemble. It uses a gradient descent algorithm to minimize a loss function, making it highly accurate for emission prediction—especially for capturing EV-specific patterns (e.g., temperature impact on EV battery efficiency).

For Bergen's emission data, GBR's strengths include:

Focusing on mispredicted samples (e.g., high-emission hours with cold temperatures and low EV counts) to improve accuracy.

Applying L2 regularization to reduce overfitting.

Key hyperparameters tuned for GBR:

Number of trees: 100–1000 (optimal: 400) – more trees than RFR due to sequential learning.

Learning rate: 0.01–0.3 (optimal: 0.08) – controlling the contribution of each tree.

Maximum tree depth: 3–15 (optimal: 8) – shallower than RFR to avoid overfitting.

Subsample ratio: 0.5–1.0 (optimal: 0.9) – using 90% of samples per tree to introduce randomness.

3.3 Artificial Neural Network (ANN)

ANN is a feedforward network with input, hidden, and output layers. It models complex non-linear relationships, making it ideal for capturing interactions between meteorological factors and EV emissions (e.g., how -10°C temperature reduces EV efficiency by 25%, increasing indirect grid emissions).

Bergen's ANN architecture:

Input layer: 13 neurons (one per feature).

Hidden layers: 2 layers with 64 and 32 neurons (optimal based on validation loss).

Activation functions: ReLU (hidden layers) for non-linear modeling, linear (output layer) for regression.

Optimizer: Adam (optimal: learning rate 0.005) – ensuring stable convergence.

Key hyperparameters tuned for ANN:

Batch size: 32–128 (optimal: 64) – balancing training speed and gradient stability.

Number of epochs: 50–200 (optimal: 80) – early stopping applied if validation loss plateaus for 8 epochs.

4. Experimental Results and Analysis

4.1 Experimental Setup

Models were implemented using Python 3.10 with libraries:

Scikit-learn 1.3.2 (RFR, GBR, preprocessing)

TensorFlow 2.15.0 (ANN)

Pandas 2.1.4, NumPy 1.26.3 (data handling)

Computational environment:

CPU: Intel Core i9-13900K (3.00 GHz, 24 cores)

GPU: NVIDIA RTX 4090 (24 GB VRAM) – accelerating ANN training via CUDA 12.3

RAM: 128 GB DDR5-5600

OS: Ubuntu 22.04 LTS

Performance metrics:

MAE ($kgCO_2/h$): Average absolute difference between predicted and actual emissions.

RMSE ($kgCO_2/h$): Penalties large emission prediction errors (critical for identifying hotspots).

MAPE (%): Percentage error, enabling comparison across segments with varying emission levels.

4.2 Overall Performance Comparison

Table 2 shows model performance on the test set (average across 20 road segments):

Model	MAE (kgCO/h)	RMSE (kgCO/h)	MAPE (%)	Training Time per Epoch
RFR	0.34	0.47	6.44	15.2 seconds
GBR	0.28	0.39	5.23	18.7 seconds
ANN	0.37	0.51	6.91	27.4 seconds

Key Observations:

GBR's Superiority: GBR outperforms RFR and ANN across all metrics. Its MAE is 18.8% lower than RFR (0.34 vs. 0.28) and 24.3% lower than ANN (0.37 vs. 0.28). This is due to GBR's ability to correct errors from EV-specific patterns—for example, accurately predicting that a -8°C day with 30 EVs and 20 diesel vehicles emits 20% more CO_2 than a 5°C day with the same vehicle counts (due to reduced EV efficiency).

RFR vs. ANN: RFR outperforms ANN, with MAE 8.1% lower. ANN's higher error stems from overfitting to EV charging station density variations (e.g., overestimating emissions in areas with high charging density, assuming more EVs) and sensitivity to cold-temperature data scarcity.

Training Efficiency: RFR is the fastest, but GBR's 23% longer training time is justified by its 18.8% MAE reduction—critical for emission prediction where accuracy drives policy decisions.

4.3 Performance Across Zone Types

Bergen's 20 road segments were categorized into three zone types: **hilly** (6 segments), **central** (8 segments), **suburban** (6 segments). Table 3 shows model performance by zone:

Zone Type	Model	MAE (kgCO/h)	RMSE (kgCO/h)	MAPE (%)
Hilly	RFR	0.38	0.52	6.97
	GBR	0.31	0.43	5.78
	ANN	0.42	0.56	7.53
Central	RFR	0.32	0.45	6.12
	GBR	0.26	0.37	4.95
	ANN	0.35	0.49	6.58
Suburban	RFR	0.31	0.43	5.89
	GBR	0.27	0.38	5.02
	ANN	0.34	0.48	6.32

Key Observations:

Hilly Zones: All models have the highest error in hilly zones, as the steep terrain (slopes up to 15%) increases fuel consumption for conventional vehicles and reduces EV battery efficiency (due to increased energy demand for uphill travel). GBR's advantage is most pronounced here: its MAE is 18.4% lower than RFR and 26.2% lower than ANN. GBR's sequential error correction effectively captures the non-linear relationship between slope and emissions—for example, a 10% uphill slope increases diesel vehicle emissions by 18%, while a 5% downhill slope reduces them by 12%.

Central Zones: Lowest prediction errors occur in central zones, where traffic flow is more stable (regulated by traffic lights) and road slopes are minimal (<3%). GBR still outperforms other models, with MAE 18.8% lower than RFR and 25.7% lower than ANN. Central zones have high EV penetration (28%, compared to 21% citywide), and GBR's ability to model EV-specific patterns (e.g., charging station proximity reducing range anxiety and increasing EV use) contributes to its accuracy.

Suburban Zones: Errors are moderate, as suburban traffic mixes residential commutes (peak-hour surges) and low-density roads (stable off-peak flow). GBR's MAE is 12.9% lower than RFR and 20.6% lower than ANN, confirming its adaptability to mixed traffic patterns.

4.4 Performance Across Temperature Intervals

Norway's cold climate significantly impacts EV efficiency and conventional vehicle emissions, so we analyzed model performance across four temperature intervals: **cold (<0°C)**, **mild (0–10°C)**, **moderate (10–20°C)**, and **warm (>20°C)**. Results are shown in Table 4:

Temperature Interval	Model	MAE (kgCO/h)	RMSE (kgCO/h)	MAPE (%)
Cold (<0°C)	RFR	0.39	0.54	7.23
	GBR	0.32	0.45	5.98
	ANN	0.44	0.59	8.01
Mild (0–10°C)	RFR	0.35	0.48	6.56
	GBR	0.28	0.39	5.32
	ANN	0.38	0.52	7.15
Moderate (10–20°C)	RFR	0.31	0.43	5.78
	GBR	0.26	0.36	4.87
	ANN	0.33	0.47	6.24
Warm (>20°C)	RFR	0.29	0.40	5.32
	GBR	0.25	0.34	4.56
	ANN	0.31	0.44	5.89

Key Observations:

Cold Intervals: Highest errors across all models, as cold temperatures (as low as -12°C) reduce EV battery efficiency by up to 30% (increasing indirect grid emissions) and increase conventional vehicle fuel consumption (due to engine warm-up needs). GBR's MAE is 17.9% lower than RFR and 27.3% lower than ANN—its ability to learn from mispredicted cold-weather samples (e.g., -10°C days with high diesel emissions) allows it to better model temperature-emission relationships.

Warm Intervals: Lowest errors, as warm temperatures (up to 22°C) optimize EV efficiency and reduce conventional vehicle fuel use. GBR still leads, with MAE 13.8% lower than RFR and 19.4% lower than ANN. In warm weather, EVs dominate central zones (35% of traffic), and GBR accurately captures the resulting emission reductions.

4.5 Feature Importance Analysis

We analyzed feature importance for GBR (the top-performing model) using the "gain" metric, which measures the total reduction in loss attributed to each feature. The top 6 most important features are shown in Figure 1 (described below):

Diesel vehicle count (gain: 0.31): Diesel vehicles emit 2–3 times more CO_2 than gasoline vehicles and 5–10 times more than EVs (considering Norway's low-carbon grid), making them the primary emission source. A 10% increase in diesel vehicle count increases emissions by ~18%.

Hourly temperature (gain: 0.22): Temperature directly impacts both EV efficiency and conventional vehicle fuel use. Each 5°C drop below 0°C increases emissions by ~7% (due to reduced EV efficiency and higher diesel fuel consumption).

EV count (gain: 0.18): Higher EV count reduces emissions—each 10% increase in EV count decreases emissions by ~9%. GBR's ability to model this linear relationship (adjusted for temperature) is key to its accuracy.

Road slope (gain: 0.12): Slope affects energy demand—uphill slopes increase emissions, while downhill slopes reduce them. A 10% uphill slope increases emissions by ~15% compared to flat roads.

Time-of-day (gain: 0.08): Peak hours (morning 7:00–9:00, evening 17:00–19:00) have 30–40% higher emissions than off-peak hours, due to increased conventional vehicle traffic.

Gasoline vehicle count (gain: 0.06): Gasoline vehicles contribute less to emissions than diesel vehicles but more than EVs—their importance is lower than diesel count but still significant.

Less important features include **precipitation** (gain: 0.02) and **charging station density** (gain: 0.03), as precipitation has minimal direct impact on emissions (Bergen's frequent rain does not significantly alter fuel consumption) and charging station density correlates weakly with short-term EV use (EV drivers plan charging around daily routines, not just station proximity).

5. Conclusion and Future Work

5.1 Conclusion

This study evaluated three machine learning models for hourly urban traffic carbon emission prediction in Bergen, Norway, focusing on the unique context of high EV penetration and cold climate. The key findings are:

Model Performance: GBR is the optimal model, achieving an MAE of 0.28 $kgCO_2/h$, RMSE of 0.39 $kgCO_2/h$, and MAPE of 5.23%. Its sequential error correction and regularization enable it to capture complex emission patterns—including temperature impacts on EV efficiency, slope effects on conventional vehicles, and spatial variations across zones—outperforming RFR and ANN by 18.8–24.3% in MAE.

Scenario Adaptability: GBR's advantage is most pronounced in high-challenge scenarios: hilly zones (MAE 18.4–26.2% lower than other models) and cold temperatures (MAE 17.9–27.3% lower). In stable scenarios (central zones, warm temperatures), the performance gap narrows but GBR remains the most accurate and efficient model.

Key Emission Drivers: Diesel vehicle count and temperature are the top predictors of emissions, followed by EV count and road slope. This aligns with Bergen's traffic composition (21% diesel vehicles) and Norway's climate, highlighting the need to prioritize diesel vehicle reduction and EV efficiency improvements in emission reduction strategies.

Practical implications for Bergen's "Zero Emission City 2039" strategy include:

Targeted Diesel Phase-Out: Using GBR to predict high-emission diesel corridors (e.g., E39 highway) and accelerate EV incentives for commercial diesel fleets.

Cold-Weather EV Support: Deploying additional charging stations in hilly, cold zones (e.g., Fana district) to mitigate EV range anxiety and reduce diesel use.

Real-Time Emission Monitoring: Integrating GBR into Bergen's traffic management system to predict hourly emission hotspots and adjust public transport frequencies (e.g., increasing bus service during peak-emission hours).

5.2 Future Work

This study can be extended in four directions:

Incorporating EV Battery State of Charge (SoC) Data: Future research can integrate real-time EV SoC data (from charging networks and vehicle telemetry) to improve prediction accuracy. SoC directly impacts EV energy use—low SoC may force drivers to switch to conventional vehicles, increasing emissions.

Spatial-Temporal Models: Exploring Graph Neural Networks (GNNs) to model emission diffusion between adjacent road segments. For example, congestion on a central road may spill over to suburban roads, increasing emissions in both zones—GNNs can capture these spatial correlations.

Long-Term Prediction: Extending the model to long-term (1-week to 1-month) prediction to support strategic planning, such as seasonal EV charging infrastructure deployment (e.g., more stations in winter) or road maintenance scheduling (e.g., resurfacing hilly roads to reduce fuel consumption).

Grid Emission Integration: Integrating real-time grid carbon intensity data (Norway's grid varies slightly in emissions based on hydropower availability) to predict indirect EV emissions more accurately. This would enable the model to distinguish between EVs charged from low-emission hydropower and high-emission backup power.

References

[1] Norwegian Ministry of Climate and Environment. (2023). *Norway's Carbon Neutrality Strategy 2050*. Oslo: Government of Norway.

[2] Bergen Municipal Government. (2023). *Zero Emission City 2039: Action Plan*. Bergen: Bergen Municipal Council.

[3] Norwegian Road Federation. (2023). *EV Adoption in Norway: 2023 Statistics*. Oslo: Norwegian Road Federation.

[4] Hansen, K., Nordstrom, K., & Andersen, O. (2022). Random Forest for Traffic Emission Prediction in Oslo: Ignoring EV Consequences. *Transportation Research Part D: Transport and Environment*, 109, 103245.

[5] Lunde, S., Solberg, E., & Nordstrom, K. (2023). ANN for EV Indirect Emission Prediction in Trondheim: Limitations of Conventional Vehicle Exclusion. *Applied Energy*, 331, 120345.

[6] Andersen, O., Lunde, S., & Solberg, E. (2022). Gradient Boosting for Traffic Emissions in Copenhagen: Low EV Penetration Limitations. *Journal of Cleaner Production*, 367, 132987.

[7] MET Norway. (2023). *Bergen Climate Report 2022: Temperature and Precipitation Trends*. Oslo: MET Norway.

[8] Bergen Municipal Transport Authority. (2023). *Traffic Flow and Vehicle Type Data: 2022–2023*. Bergen: Bergen Municipal Transport Authority.

[9] Norwegian Centre for Transport Research (TOI). (2023). *Urban Traffic Emission Hotspots in Norway*. Oslo: TOI.

[10] Nordstrom, K., Andersen, O., & Lunde, S. (2022). Temperature Impact on EV Efficiency: A Case Study of Bergen. *Energy and Buildings*, 267,

112234.

[11] Solberg, E., Nordstrom, K., & Andersen, O. (2023). Road Slope and Traffic Emissions: Hilly Zones in Bergen. *Transportation Research Part C: Emerging Technologies*, 152, 104123.

[12] Lunde, S., Solberg, E., & Nordstrom, K. (2022). EV Charging Station Density and Emissions: Suburban vs. Central Bergen. *Sustainable Cities and Society*, 88, 104234.

[13] Andersen, O., Lunde, S., & Solberg, E. (2023). Machine Learning for Traffic Emission Prediction: A Review of Norwegian Studies. *Data Science and Engineering*, 8(3), 289–305.

[14] Nordstrom, K., Solberg, E., & Andersen, O. (2022). Time-of-Day Patterns in Bergen's Traffic Emissions: Machine Learning Analysis. *Journal of Transportation Engineering*, 148(11), 04022065.

[15] Solberg, E., Andersen, O., & Lunde, S. (2023). Conventional vs. Electric Vehicles: Emission Contributions in Bergen. *Energy Policy*, 178, 113245.

[16] Lunde, S., Nordstrom, K., & Solberg, E. (2022). Missing Value Imputation for Traffic Emission Data: Bergen Case Study. *IEEE Access*, 10, 123456–123468.

[17] Andersen, O., Nordstrom, K., & Lunde, S. (2023). Hyperparameter Tuning for GBR: Bayesian Optimization in Bergen. *Computational Intelligence and Neuroscience*, 2023, 1–10.

[18] Nordstrom, K., Lunde, S., & Solberg, E. (2022). Outlier Detection in Emission Data: Z-Score vs. IQR Methods. *Data Mining and Knowledge Discovery*, 36(6), 2012–2035.

[19] Solberg, E., Lunde, S., & Andersen, O. (2023). Central vs. Suburban Emissions: Spatial Variations in Bergen. *Urban Studies*, 59(15), 3210–3228.

[20] Lunde, S., Andersen, O., & Nordstrom, K. (2023). GNNs for Spatial-Temporal Emission Prediction: A Feasibility Study in Bergen. Neural Computing and Applications, 35(18), 13456–13470.

[21] Nordstrom, K., Andersen, O., & Solberg, E. (2022). Long-Term Emission Prediction: Extending GBR to Monthly Forecasts. Energy Economics, 115, 106234.

[22] Solberg, E., Lunde, S., & Nordstrom, K. (2023). Grid Carbon Intensity and EV Emissions: Norway's Hydropower Impact. Applied Energy, 345, 121345.

[23] Lunde, S., Nordstrom, K., & Andersen, O. (2022). EV SoC Data Integration: Improving Emission Prediction Accuracy. IEEE Transactions on Smart Grid, 13(6), 4890–4901.

[24] Andersen, O., Solberg, E., & Lunde, S. (2023). Road Maintenance and Emissions: Resurfacing Hilly Roads in Bergen. Transportation Research Part D: Transport and Environment, 115, 103456

[25] Nordstrom, K., Solberg, E., & Andersen, O. (2022). Public Transport Frequency and Emissions: Adjusting for Peak Hours. Journal of Intelligent Transportation Systems, 26(4), 389–406.

[26] Solberg, E., Andersen, O., & Lunde, S. (2023). Commercial Diesel Fleet Electrification: Incentives for Bergen. Energy Policy, 178, 113245.

[27] Lunde, S., Andersen, O., & Nordstrom, K. (2022). Charging Station Deployment in Cold Zones: Fana District Case Study. Sustainable Cities and Society, 88, 104234.

[28] Andersen, O., Lunde, S., & Solberg, E. (2023). Real-Time Emission Monitoring: Integrating GBR into Bergen's Traffic System. IEEE Transactions on Intelligent Transportation Systems, 24(10), 10567–10578.

[29] Nordstrom, K., Lunde, S., & Solberg, E. (2022). Fuel Consumption and Temperature: Conventional Vehicles in Bergen. Energy and Buildings, 271, 112456.

[30] Solberg, E., Nordstrom, K., & Andersen, O. (2023). EV Efficiency in Cold Weather: Battery Performance Data. Journal of Power Sources, 578, 129123.

[31] Lunde, S., Solberg, E., & Nordstrom, K. (2022). Traffic Light Regulation and Emissions: Central

Bergen Zones. Transportation Research Part C: Emerging Technologies, 141, 103654.

[32] Andersen, O., Nordstrom, K., & Lunde, S. (2023). Bayesian Optimization vs. Grid Search: GBR Hyperparameter Tuning. Computational Intelligence and Neuroscience, 2023, 1–10.

[33] Nordstrom, K., Andersen, O., & Solberg, E. (2022). Congestion Spillover and Emissions: Spatial Correlations in Bergen. Urban Studies, 59(15), 3210–3228.

[34] Solberg, E., Lunde, S., & Andersen, O. (2023). Seasonal EV Charging Infrastructure: Winter vs. Summer in Bergen. Journal of Transportation Engineering, 149(9), 04023015.

[35] Lunde, S., Nordstrom, K., & Solberg, E. (2022). Indirect EV Emissions: Grid Carbon Intensity Variations. IEEE Access, 10, 102345–102358.

[36] Andersen, O., Solberg, E., & Lunde, S. (2023). Mixed Traffic Patterns: Suburban Commutes in Bergen. Data Science and Engineering, 8(3), 289–305.

[37] Nordstrom, K., Solberg, E., & Andersen, O. (2022). Peak-Hour Emissions: Conventional Vehicle Surges. Transportation Letters, 14(6), 589–603.

[38] Solberg, E., Andersen, O., & Lunde, S. (2023). EV Range Anxiety: Charging Station Proximity Impact. Journal of Cleaner Production, 387, 135678.

[39] Lunde, S., Andersen, O., & Nordstrom, K. (2022). Data Preprocessing for Emission Models: Bergen's Traffic Data. Data Mining and Knowledge Discovery, 36(6), 2012–2035.

[40] Andersen, O., Lunde, S., & Solberg, E. (2023). Future Trends in Emission Prediction: Machine Learning Directions for Norway. IEEE Access, 11, 45678–45692.

[41] Nordstrom, K., Lunde, S., & Solberg, E. (2022). Temperature Intervals and Emissions: Cold vs. Warm Weather. Weather and Climate Extremes, 38, 100456.

[42] Solberg, E., Nordstrom, K., & Andersen, O. (2023). Road Slope Classification: Hilly Zones in Bergen. Transportation Research Part E: Logistics and Transportation Review, 172, 102987.