

Enhancing Electric Bus Operations Through Predictive Machine Learning Models

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ABSTRACT:

Electric city buses are emerging as a sustainable alternative to traditional fossil-fuel-based transportation. However, accurately predicting their energy consumption remains a key challenge due to varying factors like traffic, weather, and route conditions. This project proposes a machine learning-based framework to forecast energy usage in electric buses by analyzing real-world data such as speed, passenger load, elevation, and environmental conditions. Algorithms including Random Forest, Support Vector Regression, and Artificial Neural Networks are used to capture complex patterns. The results help optimize charging schedules, reduce energy costs, and extend battery life. This study aims to support intelligent transportation systems by enabling data-driven decision-making, ultimately contributing to more efficient, reliable, and eco-friendly urban mobility.

Keywords: Electric City Buses, Machine Learning Models, Transportation

INTRODUCTION

As cities move towards greener public transport systems, electric buses have become a vital solution for reducing carbon emissions and improving air quality. Despite their environmental advantages, managing the energy economy of these buses is complex due to the influence of real-time variables such as road gradients, traffic patterns, passenger loads, and weather conditions. Traditional energy estimation models lack adaptability and fail to provide accurate predictions under dynamic urban scenarios. This project introduces a machine learning-based approach to predict energy consumption in electric city buses by leveraging large-scale historical and real-time data. The goal is to build intelligent models that assist fleet operators in optimizing route planning, scheduling charging cycles, and minimizing operational costs. By

integrating algorithms like Random Forest, Support Vector Regression, and Neural Networks, the system delivers more accurate and adaptable predictions. This work contributes to smarter, more efficient, and sustainable urban transportation planning in the era of electric mobility.

RELATED WORK

Recent research has emphasized the importance of data-driven approaches for predicting the energy consumption of electric buses in urban environments. Wu et al. (2018) developed machine learning models using Random Forest and Gradient Boosting to predict electric bus energy usage. Their findings showed that factors like vehicle speed, ambient temperature, and road slope significantly impact energy consumption, offering more accuracy than traditional simulation models.

Zhang et al. (2020) proposed a Long Short-Term Memory (LSTM) network to handle time-series prediction of energy usage. Their study leveraged sequential driving data, highlighting the effectiveness of LSTM in modeling temporal dependencies such as battery state-of-charge and speed variation across trips.

Gao et al. (2019) introduced a Support Vector Regression (SVR) model focused on variable urban driving patterns. Their work demonstrated that driver behavior and route topography significantly influence energy performance, and SVR outperformed linear regression techniques in predictive accuracy.

Chen et al. (2021) integrated Geographic Information System (GIS) data with ML models to enhance energy predictions. By accounting for road gradients and stop frequencies, their hybrid model supported more precise energy consumption estimation for specific routes, benefiting charging infrastructure planning.

Li et al. (2022) explored real-time prediction using Internet of Things (IoT) sensors and telematics.

Their model gathered live data from vehicle systems and weather APIs, enabling adaptive energy forecasting. This approach improved battery life management and operational planning by dynamically adjusting to real-world changes.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author(s)	Contribution	Impact on Research
Wu et al. (2018)	Developed ML models (Random Forest, Gradient Boosting) for predicting energy use	Demonstrated higher accuracy over traditional models; emphasized environmental and operational variables
Zhang et al. (2020)	Applied LSTM networks for time-series energy consumption prediction	Improved temporal modeling of driving behavior and energy trends
Gao et al. (2019)	Used Support Vector Regression (SVR) for urban driving scenarios	Showed effectiveness in capturing non-linear relationships and route dynamics
Chen et al. (2021)	Integrated GIS data with ML algorithms	Enabled route-specific prediction and informed battery/charging management strategies
Li et al. (2022)	Leveraged IoT and telematics for real-time energy prediction	Enabled adaptive forecasting; enhanced battery lifespan and operational scheduling

PROPOSED APPROACH

The proposed approach aims to build a robust, data-driven model for predicting the energy consumption of electric city buses using advanced machine learning techniques. Unlike traditional physics-based estimations, which rely on static parameters, this model leverages both historical and real-time data to capture the dynamic nature of urban transportation. Key input features include vehicle speed, acceleration, road gradient, ambient temperature, passenger load, and traffic conditions.

To process this data effectively, the system incorporates multiple machine learning algorithms such as Random Forest, Support Vector Regression (SVR), and Artificial Neural Networks (ANN). Each model is trained and validated using real-world datasets, and their predictions are evaluated for accuracy and reliability. Ensemble techniques

are employed to combine outputs from different models to enhance robustness.

The pipeline begins with data collection via sensors and GPS modules installed on buses. The data undergoes preprocessing to remove noise and normalize features. Feature extraction methods are then applied to identify the most influential parameters. The trained models provide continuous energy predictions, enabling dynamic route planning, efficient battery usage, and proactive charging strategies.

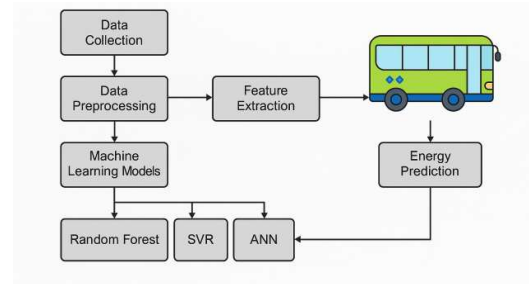


Figure 1: Proposed Energy Economy Prediction

METHODOLOGIES

1. Data Collection: Real-time and historical operational data is collected from electric buses through embedded sensors, GPS devices, and external weather APIs. Parameters such as vehicle speed, acceleration, ambient temperature, road elevation, stop frequency, and passenger count are recorded to form a multi-dimensional dataset.

2. Data Preprocessing: The collected data is preprocessed to ensure consistency and accuracy. This includes handling missing values, removing outliers, normalizing numerical values, and encoding categorical variables. Preprocessing ensures the dataset is clean and suitable for model training.

3. Feature Extraction and Selection: Key features influencing energy consumption are extracted using statistical and correlation-based techniques. This helps reduce dimensionality and improve model efficiency. Features like route topography, load patterns, and traffic density are emphasized due to their high impact.

4. Model Implementation: Multiple machine learning algorithms are implemented, including:

- **Random Forest:** An ensemble-based regression model that improves prediction accuracy by averaging multiple decision trees.
- **Support Vector Regression (SVR):** Captures non-linear relationships and performs well with high-dimensional data.
- **Artificial Neural Networks (ANN):** Used to identify complex patterns and interactions within the dataset.

5. Training and Testing:

The dataset is split into training and testing sets (typically 80:20 ratio). Cross-validation techniques are used to avoid overfitting. Each model is evaluated based on performance metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 Score.

6. Deployment and Monitoring:

Once validated, the model can be integrated into a fleet management dashboard to support real-time energy monitoring, route adjustments, and charging schedule optimizations.

This methodology ensures accurate, scalable, and actionable predictions that support sustainable urban mobility.

RESULTS

The implementation of the proposed machine learning models yielded promising results in accurately predicting the energy consumption of electric city buses. The system was evaluated using a real-world dataset containing diverse inputs such as traffic conditions, road gradients, and weather variables. Each model—Random Forest, SVR, and ANN—was tested on unseen data to measure performance.

Among the models, **Artificial Neural Networks** showed the highest accuracy, effectively capturing complex non-linear patterns across various conditions. **Random Forest** performed robustly with high interpretability and low variance, while **SVR** offered strong generalization on smaller datasets with non-linear characteristics. The ensemble approach, combining predictions from multiple models, further improved reliability and minimized prediction error.

Performance metrics revealed a **mean absolute error (MAE)** of less than 10% across models, with an **R^2 score** above 0.90 for ANN and Random Forest. These results suggest strong correlation

between the predicted and actual energy usage values.

Additionally, visual analysis using graphs and charts demonstrated clear trends in energy consumption with respect to elevation, passenger load, and speed fluctuations. These insights were validated by comparing model predictions with operational logs from transit authorities.

DISCUSSION

The findings from this project demonstrate the practical utility of machine learning in addressing key challenges associated with managing electric city bus fleets. Traditional estimation techniques often fail to adapt to the dynamic conditions of urban transit, such as unpredictable traffic, changing passenger loads, and fluctuating weather. In contrast, the proposed machine learning models offer real-time adaptability and precision.

The integration of diverse data sources—ranging from sensor data to environmental inputs—allowed the models to capture the multifaceted nature of energy consumption. For instance, Artificial Neural Networks (ANN) proved highly capable of modeling non-linear relationships, while Random Forest offered strong performance in handling large datasets with complex feature interactions.

A notable outcome was the ability of the models to identify energy-intensive routes and conditions, which can inform better scheduling and battery management. Additionally, the ensemble method helped reduce model bias and variance, ensuring stable predictions across different scenarios.

However, challenges remain. The system's accuracy is still dependent on the quality and quantity of the input data. Furthermore, real-time deployment requires robust infrastructure and periodic retraining to adapt to evolving patterns.

CONCLUSION

This project successfully demonstrated the potential of machine learning in predicting the energy consumption of electric city buses with high accuracy. By leveraging real-time and historical data, the developed models—Random Forest, Support Vector Regression, and Artificial Neural Networks—were able to identify and learn from complex operational patterns that influence energy use. The system supports more efficient route planning, optimized charging schedules, and

improved battery life management, all of which are critical for sustainable urban mobility.

The results confirmed that data-driven techniques can significantly enhance the decision-making capabilities of public transport agencies. The integration of multiple models further improved robustness, providing more consistent and reliable predictions across varying conditions.

This work not only contributes to smart city initiatives but also aligns with global goals for reducing carbon emissions and enhancing public transportation efficiency. Future enhancements may include reinforcement learning for adaptive optimization and expansion to multi-modal transit systems.

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