Driver Behavior–Based Optimization of Electric Bus Energy Consumption via Bio-Inspired WUTP Algorithm and Real-Time Data Analytics

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Abstract. The transition toward sustainable urban transportation necessitates not only advances in electric bus (E-Bus) technology but also the optimization of operational variables that directly affect system efficiency. Among these factors, driver behavior plays a pivotal role in determining energy consumption and overall range performance. This study presents an advanced artificial intelligence–based optimization framework that combines real-time big data analytics with a bio-inspired algorithm modeled on Water Uptake and Transport in Plants (WUTP). The proposed system was applied to hybrid trolleybus-type E-Buses operating in Malatya, Turkey, utilizing a dataset of approximately 50 million measurements collected under varying climatic, topographical, and operational conditions. After comprehensive preprocessing and correlation analysis, fourteen dominant parameters—including regenerative braking rate, auxiliary loads (HVAC and static converters), acceleration, and road gradient—were identified as the principal contributors to energy usage. Using a representative dataset of 60,000 samples, the WUTP algorithm generated optimized driving patterns and adaptive weighting coefficients, allowing the estimation of ideal operational thresholds. The results demonstrate that sustaining regenerative braking efficiency above 77%, maintaining moderate accelerator input around 44%, and ensuring steady vehicle speed significantly enhance driving range while lowering energy demand. Comparative driver analyses revealed performance variations exceeding 30%, emphasizing the necessity for intelligent training and monitoring systems. The developed framework, characterized by its adaptability to different routes and environmental conditions, offers a scalable tool for fleet energy management, eco-driving evaluation, and battery capacity planning in sustainable public transportation networks.

Keywords: Regenerative braking systems, Big data in transportation, Transport energy efficiency, Sustainable urban mobility, Artificial intelligence in transit systems.

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1 Introduction

The intensifying global climate crisis and the pursuit of sustainability objectives demand substantial transformations within the transportation sector. Road transport remains one of the primary sources of greenhouse gas (GHG) emissions and energy demand worldwide. Among various transport modes, internal combustion engine (ICE) vehicles are particularly responsible for deteriorating air quality in urban environments. Consequently, the transition toward low-carbon mobility options, notably electric buses (e-buses), has become a strategic priority. Substituting conventional diesel buses with e-buses effectively eliminates tailpipe emissions, thereby contributing to a significant reduction in particulate pollutants in cities [1]. When the electricity used for charging is generated from renewable energy sources (RES), the environmental and energy security advantages are further amplified. Empirical assessments indicate that e-buses can achieve petroleum savings exceeding 85% compared with diesel vehicles. On a life-cycle basis, the utilization of fossil fuels decreases by approximately 30–45%, accompanied by CO_2 emission reductions of 20–35% [2,3]. These statistics underline the potential of e-buses to advance sustainable urban transport and diminish dependence on nonrenewable energy.

Nevertheless, sustaining high operational efficiency in e-bus fleets remains a multifaceted challenge. In addition to technological aspects such as battery chemistry and charging infrastructure, numerous external parameters—including traffic congestion, route gradient, stop frequency, ambient conditions, and auxiliary power demands from heating, ventilation, and air conditioning (HVAC) systems—affect overall energy consumption. Among these determinants, driver behavior has emerged as a particularly influential yet often underestimated variable. Behavioral patterns such as acceleration aggressiveness, braking intensity, cruising consistency, and anticipatory driving are known to strongly influence vehicle energy efficiency. Consequently, optimizing e-bus energy performance necessitates not only advancements in technology but also behavioral adaptation.

Recent research has increasingly emphasized the significance of driver-induced variability in energy use [1,4,5]. As a result, the modeling and prediction of e-bus energy consumption have become prominent areas of investigation. Modeling strategies typically fall into three main categories: (i) physics-based models, which simulate energy flow through vehicle subsystems; (ii) empirical models, constructed from measured or simulated operational data; and (iii) hybrid models, which integrate physical modeling with data-driven techniques for improved predictive fidelity. Despite methodological differences, all approaches share the objective of representing the complex and dynamic influences on e-bus energy consumption under realistic driving conditions while maintaining computational efficiency. A comprehensive understanding of these interdependent variables—particularly driver behavior—is essential for enhancing fleet-level energy management, alleviating range limitations, and advancing sustainable transportation objectives. This growing recognition has established driver-centric energy modeling as a critical and rapidly developing research domain.

2 Literature Review

Recent studies have highlighted the substantial influence of driver behavior on electric bus (e-bus) energy consumption, particularly during acceleration and deceleration phases. Research [6] investigating departures from bus stops revealed that energy usage during acceleration can account for up to 47% of total consumption, with driver variability contributing nearly 29% of this effect. These differences become more pronounced at higher speeds, emphasizing the critical role of driving style. Similarly, multivariate analyses of electric vehicle energy demand [7] using Monte Carlo simulations across diverse driving cycles identified vehicle-specific factors such as drag coefficient, mass, and rolling resistance as primary contributors. Aggressive driving behaviors were found to increase energy consumption, while improvements in regenerative braking efficiency could partially mitigate this effect.

Fleet-level studies have further corroborated these findings. An investigation of 13 BYD K9UD buses in Hungary [8] using FleetLink data indicated that HVAC energy use alone reached 50–70% during winter conditions, and driver behavior accounted for a 31.85% difference between the most and least efficient operators. Long-term monitoring of battery cell voltages was also recommended to prevent operational risks. Another field study [3] analyzing 187 routes over 18 days demonstrated that driver behavior contributed to 50% of motor energy consumption, with aggressive acceleration increasing energy use and hard braking enhancing regenerative recovery.

Recent predictive approaches have leveraged advanced data-driven models. Transformer-based architectures [9] integrating road network and meteorological information achieved improved energy consumption forecasts, with errors reduced by 1–39% compared to conventional methods. Other studies [10] combined multiple linear regression and Gaussian mixture models within an XGBoost framework, achieving a 7.62% reduction in mean absolute percentage error through hyperparameter optimization. Eco-driving analyses [5] highlighted that controlling accelerator pedal opening and limiting acceleration could save 15–20% of energy during stop entry and exit phases, which collectively account for nearly half of total energy consumption. Collectively, these investigations underscore the importance of considering driver behavior alongside environmental and vehicular factors to optimize e-bus energy efficiency and support sustainable urban mobility.

2.1 Contribution of this study to the literature

This study investigates the influence of driving behavior on the energy efficiency and operational range of electric buses through a real-world, data-driven approach. Unlike conventional research relying on standardized driving cycles (e.g., NEDC, HWFET, FUDS) and static simulation models, this work integrates dynamic auxiliary loads and HVAC operations using an AI-based predictive framework. Real-time data from hybrid electric buses operating under diverse environmental and topographical conditions were utilized to develop the WUTP-EBREM model, an adaptation of the Uptake and Transport in Plants algorithm for large-scale energy optimization. From 50 million data points, 60,000 representative samples were used for model training and validation, yielding superior predictive performance compared to traditional regression techniques. The model enables route-level energy assessment, identifies high-consumption segments, and offers adaptable optimization strategies for seasonal and geographical variations. Overall, WUTP-EBREM provides an advanced analytical tool for enhancing driving efficiency, extending vehicle range, and improving environmental sustainability in urban electric bus operations.

3 Material and Methods

The methodology of this study begins with a detailed characterization of the E-Bus system, which served as the foundation for the dataset. Real-time operational data were collected from hybrid E-Buses operating under field conditions, encompassing nearly 50 million raw entries. After data acquisition, preprocessing and feature selection procedures were applied to extract 14 critical parameters affecting energy consumption, resulting in approximately 60,000 representative records. Subsequently, a mathematical framework was established using the Uptake and Transport in Plants (WUTP) algorithm to determine the optimal energy consumption profile for E-Bus operations. Finally, the driving behaviors of six operators along a predefined route were analyzed, enabling a comparative evaluation of their efficiency in terms of energy utilization.

The E-Bus considered in this research operates in a dual-mode configuration, utilizing both overhead catenary lines and an onboard battery, typical of trolleybus systems deployed in Malatya, Turkey since 2015. The vehicle has an unladen mass of 23,700 kg, a length of 24.7 meters, and is powered by two 250 kW electric motors supported by a 110 kWh battery pack. Operational voltages range from 600 V DC in battery mode to 750 V DC when connected to the catenary, regulated by an inverter system operating between 480–800 V DC. The fleet of 22 buses serves a 38-kilometer route segmented into four sectors: rural, urban, highway, and university zones, with 46 stops in total. Key operational metrics—duration, average speed, peak speed, and mean acceleration—were evaluated for each sector and subsequently employed as lower and upper bounds in the optimization analysis.

Data preprocessing included filtering erroneous, incomplete, or inconsistent records to ensure dataset integrity. A correlation analysis identified the most significant variables affecting energy consumption, such as recuperation power, static converter power, traction availability, brake and accelerator pedal positions, ambient temperature, road gradient, and mechanical or electrical faults. The WUTP algorithm was then applied to calculate weighting coefficients for each parameter, enabling the determination of optimal regenerative braking, braking, and acceleration ratios. Comparing actual driving patterns against the optimal model allowed the assessment of driver efficiency and identification of behaviors that minimize energy consumption and maximize driving range, providing a robust framework for operational optimization.

3.1 Modification of the WUTP Algorithm

In this study, the WUTP algorithm was integrated into the E-Bus energy consumption analysis and subsequently modified to utilize eight independent parameters as input variables. The specific adaptations of the WUTP framework are detailed in Algorithms 1 and 2. A dataset comprising 60,000 entries, stored in the Data.mat file, was employed to enable robust model training and validation.

Algorithm 1 illustrates the implementation of the E-Bus driving behavior function, in which observed energy consumption values are compared against predicted outputs derived from a linear combination of the selected input parameters. The total squared error between observed and predicted values serves as the objective function, which is minimized during the optimization process. Algorithm 2 defines the operational boundaries for all relevant vehicle parameters, including regenerative braking power, traction power, static converter output, recuperation levels, air compressor pressure, ambient temperature, acceleration, speed limits, vehicle mass, road slope, electrical and mechanical fault tolerances, and accelerator and brake pedal positions. For instance, regenerative braking is constrained to 0–407 kW, traction power ranges between 0–612 kW, and vehicle acceleration is limited to –2.4 to 1.4 m/s², while ambient temperature spans –10 °C to 45 °C. The accelerator and brake pedals are parameterized across the full 0–100% range to reflect realistic driver input.

Algorithm 1. Adding the E-Bus driving behavior function to the algorithms

```
load('Data.mat','Data');
Observed  = Data(:,14);
% Prediction
Predicted = x(1).*Data(:,1) + ...
         x(2).*Data(:,2) + ...
         .
         .
         x(14);  % constant
% Total square error
z = sum((Observed - Predicted).^2);
   end
```

Algorithm 2. Upper and lower limit of E-Bus parameters

```
case 'F25'
 fobj = @F25;
 LB= [ 0, -353, 0, 0, -2.4, 0, 24800, -21, 0, 0, 0, 0];
UB= [407, 612, 100, 10, 1.4, 67, 41900, 22, 3, 2, 100, 100];
UB=UB';
LB=LB';
Dim=14;
```

To assess the statistical validity of the model, an ANOVA analysis was performed, examining degrees of freedom (df), sum of squares (SS), mean squares (MS), and the F-statistic. The residual SS was found to be minimal relative to the total variation, indicating a strong model fit. The corresponding F-value and its associated significance level (P-value) approached zero, confirming that the regression model is statistically significant and possesses high predictive accuracy. These results validate that the WUTP-based model reliably captures the relationships between the key driving parameters and energy consumption.

Table 1. The results of the ANOVA test performed to evaluate the statistical validity of the model parameters.

	df	SS	MS	F	Significance F
Parameters	13	43338,0633	31459,78481	661,626181	2,3046e^{-67}
Difference	60000	434,145239	10,80486821		
Total	60013	134572,2086			

Overall, the integration of dynamic parameter ranges and rigorous statistical validation demonstrates that the adapted WUTP algorithm effectively predicts optimal energy consumption and driving behavior for E-Buses. This approach provides a powerful tool for fleet operators and transportation planners aiming to enhance operational efficiency, extend driving range, and optimize energy utilization under real-world operating conditions.

4 Result and Discussion

The optimization framework was developed utilizing the WUTP algorithm, configured with a population size of 50 and a maximum iteration limit of 1,000. All computational simulations and analyses were executed using MATLAB R2021b, which provided the primary platform for algorithm implementation and data processing. The resulting mathematical model, representing the system's behavior under the defined optimization conditions, is formalized in Equation (1).

$$Y = 0.0148 * P_1 + 0.0101 * P_2 - 0.0007 * P_3 + 0.7087 * P_4 + 0.1980 * P_5 - 1.3151 * P_6 + 0.0006 * P_7 - 0.0002 * P_8 + 0.0193 * P_9 + 1.6761 * P_{10} - 1.6376 * P_{11} - 0.0335 * P_{12} - 0.0607 * P_{13} - 0.8853 * P_{14} - 9.668 \quad (1)$$

In this context, Y represents the dependent variable corresponding to optimal energy consumption. The independent variables are defined as follows: P_1 denotes Regenerative Braking Power (kW), P_2 represents Static Converter Power (kW), and P_3 corresponds to Available Traction Power (kW). P_4 indicates the Retarder Level (%), P_5 is

the Air Compressor Pressure (bar), and P_6 represents the External Ambient Temperature (°C). Vehicle dynamics are captured by P_7, corresponding to Actual Vehicle Acceleration (m/s²), and P_8, representing Vehicle Speed (km/h). P_9 denotes Vehicle Weight (kg), while P_{10} specifies Road Slope (%). Fault conditions are represented by P_{11} and P_{12}, indicating Electrical and Mechanical Failures, respectively. Finally, driver control inputs are expressed as P_{13} and P_{14}, corresponding to Brake Pedal Position (%) and Accelerator Pedal Position (%).
The optimization results indicate that the numerical values assigned to each parameter represent their respective weighting coefficients. The determination of these weights was performed using a linear mapping function within the WUTP algorithm framework. Subsequently, the optimal driving conditions, derived from the WUTP-based prediction and optimization procedure, are summarized in Table 2, providing a comprehensive overview of the system's performance under ideal operational scenarios.

Table 2. Optimal driving conditions for drivers to achieve the longest driving range

	Recuperation Rate (%)	Brake Pedal Rate (%)	Accelerator Pedal Rate (%)	Vehicle Speed (km/h)	Vehicle Weight (kg)
Optimal Conditions	77.25	22.75	43.56	18.64	27,610

Table 3 summarizes the energy allocation for a 38.6 km E-Bus route with 46 stops, revealing that 77.25% of total braking energy must be captured through regenerative braking to achieve optimal driving range. This recovered energy is utilized to recharge the traction batteries, thereby enhancing the vehicle's operational efficiency. Nevertheless, certain route segments lack sufficient regenerative braking capacity, requiring conventional friction brakes to supply the remaining 22.75% of braking energy. The average vehicle speed was calculated as 18.64 km/h, while the accelerator pedal was engaged for 43.56% of total operation time. Optimal energy management also depends on maintaining the loaded vehicle mass at 27,610 kg.

Six drivers operated the E-Bus along the defined route, generating approximately 60,000 rows of real-time data encompassing vehicle dynamics, braking distribution, and energy consumption metrics. Each driver's dataset was individually analyzed using the WUTP algorithm, producing performance profiles under uniform operational conditions. This comparative assessment highlights deviations from the optimal reference model and quantifies the influence of individual driving behavior on energy efficiency. Table 3 presents driver-specific evaluations, showing variations in braking, acceleration, and overall energy utilization. These insights provide a basis for targeted interventions, including driver training, operational adjustments, or automated energy management strategies. By systematically linking observed behaviors to optimal energy profiles, the analysis supports evidence-based optimization of E-Bus operations, improving energy efficiency, extending range, and promoting sustainable urban transit.

Table 3. Driver-Specific Performance Evaluation on the E-Bus Route

Drivers / Parameters	Recuperation Rate (%)	Brake Pedal Rate (%)	Accelerator Pedal Rate (%)	Vehicle Speed (km/h)	Vehicle Weight (kg)
Driver 1	43.55	56.45	66.5	25.42	26,600
Driver 2	56.68	43.32	54.21	23.91	28,850
Driver 3	73.44	26.56	49.68	19.67	28,000
Driver 4	36.22	63.78	71.23	27.4	24,560
Driver 5	41.5	58,5	69.67	25.54	25,380
Driver 6	75.98	24,02	44.49	18.9	27,890

5 Conclusion

This study highlights the critical influence of driver behavior on the energy efficiency and operational performance of electric buses. By integrating the Water Uptake and Transport in Plants (WUTP) optimization algorithm with extensive real-world operational data, a robust analytical framework was developed to link driver actions with quantifiable energy outcomes. Findings indicate that maintaining regenerative braking contributions above 77%, moderate accelerator pedal engagement around 44%, and consistent vehicle speed can significantly reduce energy consumption while enhancing driving range. Comparative analysis across multiple drivers revealed substantial variations in efficiency attributable to individual driving styles, underscoring the value of targeted, data-driven driver training programs. The results demonstrate that optimizing human behavior is not a secondary consideration but a central element of sustainable E-Bus operations. Overall, this research confirms that AI-driven optimization of driver performance can effectively complement technological advancements in battery and powertrain design, offering actionable insights for fleet operators and urban transport planners aiming to improve energy efficiency, reduce operational costs, and support sustainable urban mobility.

References

1. Holland, S.P., Mansur, E.T., Muller, N.Z., Yates, A.J.: The environmental benefits of transportation electrification: Urban buses. *Energy Policy* **148**, 111921 (2021). https://doi.org/10.1016/J.ENPOL.2020.111921
2. Ekici, Y.E., Aydin, A.A., Karadağ, T., Akdağ, O., Ateş, A.: Energy consumption model with real-time data for driving range extension of electric buses. *Sustainable Futures* **9**, 100603 (2025). https://doi.org/10.1016/j.sftr.2025.100603
3. Zhou, B., Wu, Y., Zhou, B., Wang, R., Ke, W., Zhang, S., et al.: Real-world performance of battery electric buses and their life-cycle benefits with respect to energy consumption and carbon dioxide emissions. *Energy* **96**, 603–613 (2016). https://doi.org/10.1016/J.ENERGY.2015.12.041

4. Ekici, Y.E., Akdağ, O., Aydin, A.A., Karadağ, T.: A novel energy consumption prediction model of electric buses using real-time big data from route, environment, and vehicle parameters. *IEEE Access* **2**, 1–1 (2023). https://doi.org/10.1109/access.2023.3316362
5. Manzolli, J.A., Trovão, J.P., Antunes, C.H.: A review of electric bus vehicles research topics – Methods and trends. *Renewable and Sustainable Energy Reviews* **159**, 112211 (2022). https://doi.org/10.1016/J.RSER.2022.112211
6. Ekici, Y.E., Karadağ, T., Akdağ, O., Aydin, A.A., Tekin, H.O.: Tailoring energy efficiency for urban electric buses: The GTECM model for enhanced range and sustainable operation using real-time big data. *IEEE Transactions on Intelligent Transportation Systems* **26**, 12600–12614 (2025).
7. Lyu, A., Zhang, H., Shen, Y., Zhang, Y.: Eco-driving level evaluation model for electric buses entering and leaving stops. *IEEE Access* **13**, 71792–71805 (2025). https://doi.org/10.1109/access.2025.3561469
8. Ekici, Y.E., Karadağ, T., Akdağ, O., Aydin, A.A., Tekin, H.O.: Enhancing electric vehicle range through real-time failure prediction and optimization: Introduction to DHBA-FPM model with an artificial intelligence approach. *ICT Express* (2025). https://doi.org/10.1016/j.icte.2025.03.009
9. Yan, Y., Fan, Y.-C.: Influence of the driver style difference in the acceleration process on the energy consumption of the EV bus. In: *Proceedings of the 2016 International Conference on Energy and Advanced Transportation (ICEAT 2016)*, pp. 186–190 (2016). https://doi.org/10.2991/ICEAT-16.2017.39
10. Ekici, Y.E., Karadağ, T., Aydin, A.A., Akdağ, O.: Impact of outside temperature on driving range and energy consumption using real-time big data for electric buses. In: *8th International Artificial Intelligence and Data Processing Symposium (IDAP 2024)*, pp. 1–9 (2024). https://doi.org/10.1109/IDAP64064.2024.10710801
11. Szurke, S.K., Saly, G., Lakatos, I.: Analyzing energy efficiency and battery supervision in electric bus integration for improved urban transport sustainability. *Sustainability* **16**, 88182 (2024). https://doi.org/10.3390/su16188182
12. Ekici, Y.E., Karadağ, T., Aydin, A.A., Akdağ, O.: Impact of outside temperature on driving range and energy consumption using real-time big data for electric buses. In: *8th International Artificial Intelligence and Data Processing Symposium (IDAP 2024)*, pp. 1–9 (2024). https://doi.org/10.1109/IDAP64064.2024.10710801
13. Kang, Y., Wei, J., Liu, Z., Xiao, K.: An energy consumption prediction model for electric buses based on extreme gradient boosting fusion algorithm. *International Journal of Green Energy* **22**, 2504–2517 (2025). https://doi.org/10.1080/15435075.2025.2464155