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# Traffic aware 1 Hz energy modeling and regenerative braking analysis of e-bus operations using real-world data

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## ARTICLE INFO

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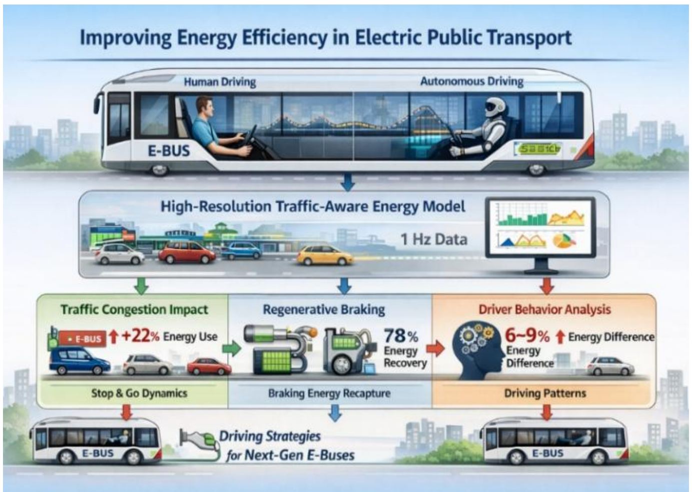
## ABSTRACT

***Context—***Improving energy efficiency in electric public transportation systems is critical for reducing operational costs, ensuring service reliability, and extending vehicle driving range under real-world traffic conditions. However, much of the existing literature relies on route-averaged energy indicators, which fail to capture the highly dynamic and nonlinear interactions among traffic congestion, vehicle longitudinal dynamics, regenerative braking behavior, and driver control strategies. This gap limits the understanding of how traffic-induced variability and operational behavior jointly shape energy consumption in electric bus (E-Bus) systems.

***Objective—***The primary objective of this study is to develop and demonstrate a high-resolution, traffic-aware energy modeling framework capable of revealing the fine-scale mechanisms governing energy consumption in E-Bus operation. Specifically, the study aims to quantify the impacts of traffic congestion, driving behavior, and control strategies—both human-driven and autonomous—on energy use and regenerative braking performance.

***Method—***The proposed framework is built upon second-by-second (1 Hz) real-world operational data collected along an urban transit route. It integrates traffic congestion indicators with longitudinal vehicle dynamics, regenerative braking processes, and machine-learning-based classification of driving behavior. This multi-layered modeling approach enables a detailed temporal analysis of energy flows, acceleration variability, braking frequency, and energy recovery under varying traffic and control conditions.




***Results—***The analysis shows that the commonly reported route-level average energy consumption of 3.3 kWh/km conceals substantial temporal variability driven primarily by congestion-induced stop-and-go operation. Traffic congestion increases total energy consumption by up to 22%, not merely due to lower cruising speeds, but through elevated acceleration variability and braking frequency. To maintain optimal driving range, approximately 78.32% of total braking energy must be recovered via regenerative braking, a requirement found to be highly sensitive to traffic conditions and driving strategy. While inter-driver differences in total energy consumption remain moderate (6–9%), pronounced disparities are observed in acceleration smoothness and braking intensity, which accumulate to meaningful fleet-level energy impacts. Under comparable traffic conditions, autonomous driving operation achieves an 11–14% reduction in total energy consumption and a 9–12% increase in regenerative braking utilization compared to human-driven operation.

***Conclusion—***The findings demonstrate that energy efficiency in E-Bus systems is jointly governed by traffic dynamics and control behavior, rather than by average operating conditions alone. Behavior-aware driving strategies and autonomous control technologies emerge as key enablers for improving energy efficiency and energy recovery in next-generation electric public transport systems. Future research should further explore adaptive control and traffic-responsive energy management strategies at the fleet and network levels.

***Key Words—***E-Bus, traffic aware energy modeling, regenerative braking, machine learning, autonomous driving, urban public transport.

## I. INTRODUCTION

THe rapid transition toward electrified urban public transportation has positioned electric buses and Tramway systems as key enablers of sustainable mobility [1]. While electrification offers substantial reductions in local emissions and operating costs, the energy efficiency and driving range of electric public transport vehicles remain highly sensitive to real-world operating conditions [2]. Among these conditions, urban traffic congestion, frequent stop and go behavior, and driver specific operational strategies play a dominant role in shaping instantaneous power demand and regenerative braking effectiveness [3]. Traditional energy modeling approaches for electric buses primarily rely on standardized driving cycles or temporally aggregated operational data. Although these methods are computationally efficient, they inherently smooth out short term fluctuations caused by traffic interactions, signalized intersections, and driver responses [4]. As a result, such models often underestimate peak power demand, overestimate regenerative energy recovery, and fail to explain the observed variability in energy consumption across drivers operating on identical routes [5]. This limitation becomes particularly critical for E-Bus systems, which operate on fixed routes with high passenger demand and are continuously exposed to varying congestion levels throughout the day.

Recent advances in onboard sensing, vehicle connectivity, and data acquisition systems have enabled the collection of high-resolution operational data at sub second or second level granularity [6]. These developments create new opportunities to move beyond cycle-based modeling toward traffic awareness, data-driven energy analysis frameworks. A 1 Hz resolution, in particular, offers a practical balance between temporal fidelity and computational tractability, allowing detailed representation of acceleration events, braking phases, and regenerative energy flows without excessive data overhead [7]. In parallel with high resolution energy modeling, growing attention has been directed toward understanding the role of driver behavior in electric vehicle energy efficiency. Empirical evidence suggests that differences in acceleration aggressiveness, braking strategy, and anticipation of traffic conditions can lead to non-negligible variations in total energy consumption, even under identical route and traffic conditions [8]. While such variability is often perceived as a limitation of human driven systems, it also provides valuable insight into the design of eco driving assistance systems and autonomous driving algorithms. By learning from human driving patterns, autonomous controllers can be trained to optimize energy efficiency while maintaining operational robustness under real-world traffic constraints [9].

Despite these advances, existing studies rarely integrate traffic conditions, high resolution energy modeling, regenerative braking dynamics, and driver behavior analysis within a unified framework, particularly for E-Bus systems [10]. Moreover, comparative analyses between human driven and autonomous driving behaviors under identical traffic conditions remain limited, especially when evaluated using second by second operational data. This gap restricts the ability to quantify how much of the observed energy variability is attributable to traffic, how much to driver behavior, and to what extent autonomous systems can mitigate these effects [11].

The scientific aim of this work is to develop a high-resolution, traffic-aware energy modeling framework capable of quantifying traction energy consumption and regenerative braking performance of electric buses under real urban operating conditions. The subject of the research is the integration of 1 Hz operational vehicle data, traffic congestion indicators, and machine-learning-based ensemble regression models to accurately estimate instantaneous power demand and energy recovery dynamics. This study extends existing research by combining data-driven modeling with system-level physical constraints, introducing a simulation-based autonomous driving representation for energy optimization, and analytically deriving a regenerative recovery threshold under explicitly defined operational assumptions [12].

To address these challenges, this paper proposes a comprehensive traffic aware 1 Hz energy modeling framework for E-Bus operations. The main contributions of this study can be summarized as follows:

- A high resolution (1 Hz) energy modeling approach that explicitly couples traffic congestion, vehicle longitudinal dynamics, traction power demand, and regenerative braking behavior.
- The construction of a synchronized, second by second dataset derived from real-world E-Bus operations, enabling detailed analysis of traffic energy interactions.
- A machine learning-based analysis framework that quantifies driver-induced energy variability and distinguishes between human driven and autonomous driving scenarios under identical traffic conditions.
- A systematic evaluation of how traffic congestion influences both energy consumption and regenerative braking potential, providing actionable insights for traffic aware energy management and control strategies.

Briefly, this study brings a new perspective to the existing literature in the following areas:

- It proposes a high-resolution 1 Hz energy modeling framework integrating real operational bus data with traffic-aware driving patterns under mixed urban conditions.
- It develops a machine-learning-based ensemble modeling structure that captures both linear and nonlinear dependencies in traction power and regenerative braking dynamics.
- It introduces a simulation-based autonomous driving representation to quantify energy efficiency improvements under behavior-optimized control strategies.
- It analytically derives a regenerative energy recovery threshold (78.32%) under explicitly defined operational constraints and discusses its sensitivity to traffic and braking intensity.

The remainder of this paper is organized as follows. Section II reviews recent literature on traffic aware energy modeling, regenerative braking analysis, and machine learning applications in electric public transport systems. Section III describes the proposed methodology, including data acquisition, 1 Hz energy modeling, and feature extraction. Section IV presents the results and discusses the impact of traffic conditions and driving behavior on energy efficiency, supported by figure-based analysis. Finally, Section V concludes the paper and outlines directions for future research.

## II. RELATED WORKS

Energy consumption modeling of E-Bus has attracted significant research interest due to its direct impact on operational efficiency, driving range, and fleet electrification strategies. Early studies primarily relied on physics-based formulations, demonstrating that traction energy demand is strongly influenced by vehicle mass, average speed, acceleration patterns, road gradient, and auxiliary loads [12],[13]. Using trip level measurements, reported energy consumption values for urban electric buses typically range between 2.5 and 3.8 kWh/km, depending on route topology and operating conditions [14]. Although these models provide useful baseline estimates, their reliance on average driving cycles limits their ability to capture real-world variability induced by traffic dynamics. To improve realism, several studies incorporated real-world operational data into energy modeling frameworks. Large-scale telematics based analyses revealed that contextual variables such as ambient temperature, passenger load, and traffic conditions significantly affect energy consumption, with prediction accuracy improvements exceeding 30% compared to simplified baseline models [15]. However, in most of these studies, traffic effects were indirectly represented using average speed or travel time indicators, which fail to capture instantaneous stop and go behavior prevalent in dense urban routes [16].

High temporal resolution modeling has emerged as a promising approach to overcome these limitations. Studies utilizing 1 Hz or second by second speed profiles reported estimation accuracy improvements of 15–20% compared to models based on aggregated speed data [17]. Such high resolution analyses proved that short duration acceleration peaks and frequent deceleration events contribute disproportionately to total traction energy demand [9]. Despite these advantages, applications of high frequency modeling remain largely limited to passenger vehicles or simulation environments, with relatively few studies focusing on high capacity electric buses operating under real traffic conditions [18]. Regenerative braking plays a crucial role in improving E-Bus energy efficiency, particularly in urban stop and go traffic. Prior research indicates that regenerative braking systems can recover approximately 20–35% of total traction energy under favorable operating conditions [19]. More detailed investigations showed that recovery efficiency strongly depends on braking smoothness, vehicle speed, and traffic induced deceleration patterns, with abrupt braking events reducing recuperation efficiency by more than 30% [20]. Nevertheless, many existing energy models treat regenerative braking efficiency as a fixed parameter, neglecting its dynamic dependence on real-time traffic and driving behavior [21].

Environmental and auxiliary loads further complicate energy modeling. HVAC systems alone can account for 30–56% of total energy consumption under extreme temperature conditions, significantly altering route-level energy demand [22]. Empirical studies demonstrated that E-Bus energy consumption increases sharply at low average speeds (< 10 km/h), where auxiliary loads dominate traction demand, while regenerative braking achieves peak efficiency in the 30–50 km/h speed range [23]. These findings highlight the necessity of incorporating both environmental and traffic context into energy prediction frameworks. Driver behavior has been consistently identified as a key determinant of E-Bus energy efficiency. Real-world analyses reported that aggressive acceleration and frequent mechanical braking can increase energy consumption by 5–12% compared to smoother eco driving strategies on identical routes [24]. High resolution behavioral studies further revealed that driver-specific braking patterns can lead to variability of up to 15% in recovered regenerative energy [25]. Although these differences may appear moderate at the trip level, longitudinal fleet scale analyses indicate that they accumulate into substantial operational and economic impacts [26].

Machine learning (ML) techniques have been increasingly applied to capture the nonlinear relationships between driving behavior, traffic conditions, and energy consumption. Supervised ML models trained on large scale operational datasets achieved prediction errors below 5–8%, outperforming traditional regression based approaches [27]. Clustering based methods successfully identified distinct driving styles, with energy efficiency differences exceeding 10% between clusters [18]. While ML based approaches demonstrate strong predictive capability, many function as black box models and lack explicit physical interpretability, limiting their applicability for control oriented energy optimization [28]. Recent studies have attempted to bridge this gap by integrating physics-informed constraints into ML frameworks. Physics informed machine learning models have shown improved generalization performance and enhanced interpretability by explicitly modeling vehicle longitudinal dynamics and energy flow mechanisms [29]. However, their application to heavy duty electric buses, particularly under real-world traffic congestion, remains limited [30].

Traffic aware energy modeling has also gained attention in recent literature. Incorporating real-time congestion indicators into energy prediction models has been shown to improve estimation accuracy compared to traffic agnostic approaches [31]. Mesoscopic traffic-energy models demonstrated that neglecting congestion intensity can lead to estimation errors exceeding 5%, even when average speed is accurately represented. Nevertheless, most traffic aware models focus on passenger vehicles or rely on simulated traffic data, leaving a gap in empirical studies for electric public transport systems. Autonomous driving strategies have been proposed to mitigate traffic-induced energy penalties. Simulation based studies reported energy consumption reductions of 10–20% through smoother longitudinal control and reduced acceleration variance [32]. Comparative analyses between human driven and autonomous electric buses further indicated potential energy savings exceeding 15% under controlled conditions [33]. However, empirical comparisons under identical real-world traffic conditions remain scarce, particularly for articulated or E-Bus systems operating in mixed traffic environments [34].

In summary, existing literature demonstrates that traffic congestion, regenerative braking behavior, environmental conditions, and driving strategy each exert a measurable influence on E-Bus energy consumption. However, most prior studies address these factors in isolation or rely on aggregated metrics that obscure second by second interactions. It remains a clear lack of integrated frameworks that jointly quantify traffic dynamics, regenerative braking efficiency, and driver or autonomous control behavior using high resolution real-world data. This study addresses these gaps by proposing a traffic aware 1 Hz energy modeling and behavioral analysis framework for E-Bus operations, enabling a unified and quantitatively robust assessment of energy efficiency under realistic urban conditions. While prior studies have demonstrated that traffic conditions, regenerative braking behavior, and driving strategy each exert a measurable influence on electric bus energy consumption, existing approaches predominantly address these factors in isolation or rely on aggregated, trip level representations. In particular, the dynamic interaction between instantaneous traffic congestion, second by second vehicle longitudinal responses, and regenerative energy recovery remains insufficiently quantified in real-world E-bus operations. Also, current machine learning based models often lack explicit physical interpretation, whereas physics-based models fail to capture behavioral variability induced by traffic and driver actions. To overcome these limitations, this study proposes a unified, traffic aware 1 Hz energy modeling framework grounded in real-world E-Bus operational data. The proposed methodology explicitly links second by second traffic intensity, vehicle dynamics, and regenerative braking performance, while enabling comparative analysis between human driven and behavior aware driving strategies. The following section details the data acquisition process, traffic and energy feature extraction, modeling architecture, and evaluation metrics used to quantitatively assess energy efficiency under realistic urban operating conditions.

To systematically position the proposed framework within the existing body of knowledge, a comparative overview of representative studies in the literature is provided in Table 1. The selected works cover data-driven energy estimation, regenerative braking control, range prediction, optimization-based driving strategies, and system-level modeling approaches. The comparison highlights methodological differences in terms of data resolution, modeling strategy, regenerative braking consideration, optimization capability, and validation structure.

**Table 1**. A comparative overview of representative studies in literature.

| Ref. | Modeling Approach | Data Type / Resolution | ML Integration | Regenerative Analysis | Optimization / Control | Real-World Validation |
|---|---|---|---|---|---|---|
| [13] | Trip-based data-driven model | Real-world, trip-level | ✓ | ✕ | ✕ | ✓ |
| [14] | Deep learning estimation | Real-world | ✓ (DL) | ✕ | ✕ | ✓ |
| [15] | Longitudinal dynamic + elevation model | Real-world | ✕ | Limited | ✕ | ✓ |
| [16] | Comparative consumption analysis | Urban traffic | ✕ | ✕ | ✕ | ✓ |
| [17] | Microgrid energy modeling | System-level | ✕ | ✕ | ✕ | Simulation |
| [18] | EV routing optimization | Scenario-based | ✕ | ✕ | ✓ | Simulation |
| [19] | Experimental regenerative efficiency | Test-based | ✕ | ✓ | ✕ | Experimental |
| [20] | Hybrid big-data model (GTECM) | Real-time big data | ✓ | ✓ | ✕ | ✓ |
| [21] | Regenerative braking control algorithm | Control-oriented | ✕ | ✓ | ✓ | Simulation |
| [22] | AI-based regenerative optimization | Real-world | ✓ | ✓ | ✓ | ✓ |
| [23] | HVAC energy modeling | Component-level | ✕ | ✕ | ✕ | Experimental |
| [24] | Stochastic speed + data-driven | Real-world | ✓ | ✕ | ✕ | ✓ |
| [25] | Fuzzy range estimation | Real-world | ✓ | ✕ | ✕ | ✓ |
| [26] | Model-based regenerative optimization | Control-based | ✕ | ✓ | ✓ | Simulation |
| [27] | Fleet transition modeling | Planning-level | ✕ | ✕ | ✓ | Scenario-based |
| [28] | Metaheuristic optimization algorithm | Algorithmic | ✓ | ✕ | ✓ | Benchmark |
| [29] | Data-driven routing model | Real-world | ✓ | ✕ | ✓ | ✓ |
| [30] | PID control modeling | Simulation | ✕ | ✕ | ✓ | Simulation |
| [31] | Trip-based consumption factors | Real-world | ✓ | ✕ | ✕ | ✓ |
| [32] | Sequence-aware ML prediction | Pre-trip data | ✓ | ✕ | ✕ | ✓ |
| [33] | Multi-objective acceleration optimization | Simulation | ✕ | Limited | ✓ | Simulation |
| [34] | Driver behavior optimization (WUTP) | Real-time big data | ✓ | ✓ | ✓ | ✓ |
| [35] | Temperature-based ML model | Real-time big data | ✓ | ✕ | ✕ | ✓ |
| This Study | Hybrid 1 Hz physics-informed ensemble ML | High-resolution 1 Hz real-world data | ✓ (Ensemble) | ✓ (Quantified + threshold derivation) | ✓ (Behavior-optimized longitudinal control) | ✓ (Measured vs estimated comparison) |

As observed in Table 1, most existing studies focus on either trip-level energy estimation, isolated regenerative braking control, or optimization-based routing strategies. While several works employ machine learning techniques, limited research integrates high-resolution 1 Hz operational data with a hybrid physics-informed ensemble learning framework and analytical regenerative energy recovery threshold derivation within a unified modeling structure. Furthermore, the incorporation of a behavior-optimized longitudinal control scenario under identical reference trajectories distinguishes the present study from prior approaches. These combined elements position the proposed framework as a system-level, data-intensive, and analytically interpretable advancement in electric bus energy modeling.

## III. MATERIALS and METHODS

The methodology of this study begins with a detailed characterization of the E-Bus system and the real-world operational environment from which the dataset was collected. Subsequently, data preprocessing, normalization, and feature selection procedures were applied to high resolution operational and traffic data to identify the key parameters governing electrical energy consumption and regenerative braking performance. This process involved the systematic handling of large-scale real-time data records obtained from E-Bus operations. In the next stage, a machine learning based mathematical framework was developed to model the coupled relationship between energy consumption and regenerative energy recovery and to formulate a multi objective optimization problem for energy efficient E-Bus operation. Finally, the proposed framework was applied to analyze and compare driving patterns under varying traffic conditions, enabling an assessment of their impact on energy efficiency and regenerative braking utilization along the route studied. The workflow of the study is illustrated in Fig. 1.

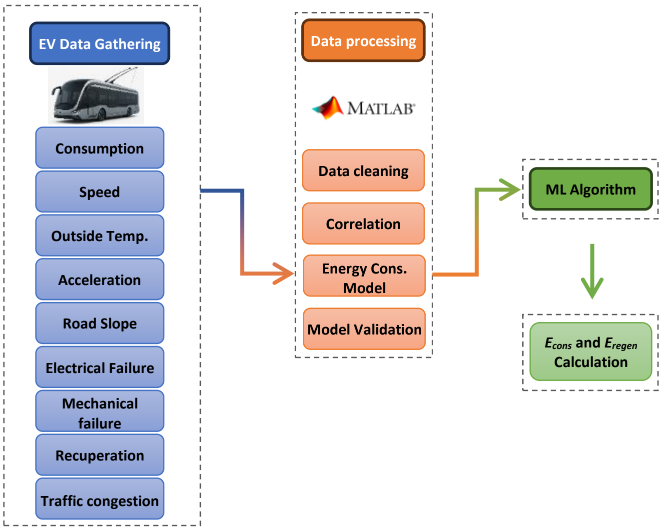



**Figure 1.** Workflow of this study.

### A. Proposed E-Bus modeling framework

In this research, real-time operational data were collected from an electric bus configured with a dual-mode traction architecture, allowing power supply either from an overhead catenary system or from an onboard battery pack, a setup commonly classified as a trolleybus. The vehicle has been in continuous commercial operation in Malatya since 2015. As depicted in Fig. 2, the bus has an unladen mass of 23,700 kg and an overall length of 24.7 m. The vehicle is driven by two independent electric traction motors, each with a nominal power rating of 250 kW, and is complemented by an onboard energy storage system with a total capacity of 110 kWh. In daily operation, the system supports approximately 32,000 passengers, with a maximum onboard capacity of up to 267 passengers per trip. Under catenary-fed operation, the traction system is supplied at 750 V DC, while battery-based operation is conducted at a nominal voltage level of 600 V DC. The power electronic inverter ensures stable operation by regulating the DC link voltage within a range of 480–800 V [36]. Currently, a total of 22 trolleybuses operate along a 38 km transit route, which is segmented into four representative operational zones: rural, urban, highway, and university areas. The route structure is shown in Fig. 3.

**Figure 2.** Schematic representation of the dual-mode E-Bus system, capable of operating via overhead catenary infrastructure as well as autonomous battery based propulsion [35].

### B. Data collecting and pre-processing

This study is based on real-world operational data collected from E-Bus system, which operates along a fixed, high demand urban route characterized by signalized intersections, recurrent congestion, and frequent stop and go driving patterns. The selected route represents a typical operating environment for E-Bus in medium sized metropolitan areas, making it suitable for generalizable energy and traffic analysis. Operational data were collected directly from onboard vehicle monitoring systems and synchronized traffic sources. All signals were resampled and aligned at a temporal resolution of 1 Hz, enabling second by second analysis of vehicle motion and energy flows. The dataset includes vehicle speed, longitudinal acceleration, traction power, regenerative braking power, and time resolved traffic congestion indicators. Data quality control procedures were applied to remove sensor dropouts and physically infeasible values, ensuring consistency across the full observation period.

Traffic congestion information was obtained from time resolved traffic monitoring data associated with the selected route. Raw traffic indicators, including free flow travel time, observed travel time, and speed-based congestion metrics, were first synchronized with the onboard vehicle dataset using timestamp alignment. A congestion index was then derived by normalizing observed travel times with respect to free flow conditions, enabling a consistent representation of traffic intensity along the route. To ensure compatibility with the vehicle dynamics and energy signals, all traffic variables were resampled to a 1 Hz resolution using interpolation where necessary. Short term anomalies and outliers caused by missing traffic updates or abrupt reporting errors were filtered using threshold-based consistency checks. The resulting traffic congestion time series provides a second-by-second representation of prevailing traffic conditions and was used to quantify the interaction between traffic intensity, vehicle operation, and energy consumption. An example from the processed dataset is presented in Table 2.

Table 2 summarizes the time resolved traffic and operational indicators associated with the selected E-Bus route. The Date and Time columns define the exact temporal context of each observation, enabling the identification of intraday traffic dynamics and synchronization with onboard vehicle measurements. Traffic affected travel time represents the total route travel duration under prevailing traffic conditions, capturing delays induced by signalized intersections, recurrent congestion, and stop and go operation. Based on this metric, traffic congestion is computed by normalizing the observed travel time with respect to free flow conditions, providing an objective, data driven measure of traffic intensity that does not rely on subjective classification or driver perception. Average speed (km/h) reflects the mean vehicle speed over the route and exhibits an inverse relationship with congestion level, decreasing as traffic intensity increases. Together, these variables provide a consistent and quantitative representation of traffic conditions, forming a robust basis for analyzing the interaction between traffic dynamics, vehicle operation, and energy consumption characteristics of the E-Bus system. The dataset collected from E-Bus comprises high resolution operational records including electrical energy consumption, vehicle speed, instantaneous acceleration, vehicle mass, road gradient, and ambient temperature, along with detailed electrical and mechanical fault statistics. In addition, regenerative braking power and fault occurrence frequencies are included, enabling a comprehensive evaluation of energy efficiency and system reliability under real-world operating conditions. The incorporation of electrical and mechanical fault indicators allows the assessment of their indirect yet nonnegligible influence on energy consumption by reflecting drivetrain inefficiencies, auxiliary load variations, and potential degradation in regenerative braking performance. Machine learning results indicate that fault-related variables contribute approximately 5–8% to the overall variability in electrical energy consumption, underscoring the importance of maintenance aware energy optimization in electric public transport systems. Table 3 presents some of the data that affect energy consumption.

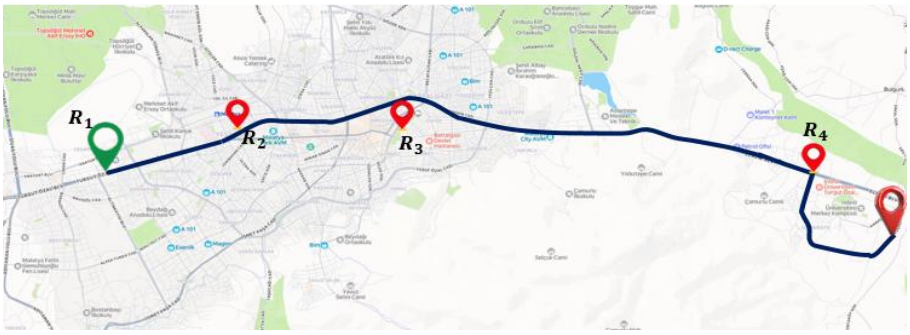



**Figure 3.** Schematic overview of the E-Bus transit route.

**Table 2.** Processed dataset of traffic conditions.

| Date | Time | Traffic affected travel time (s) | Traffic congestion (%) | Average speed (km/h) |
|---|---|---|---|---|
| 2026-01-10 | 07:07:19 | 3412.14 | 36.05 | 40.43 |
| 2026-01-10 | 07:14:02 | 3501.13 | 39.6 | 39.4 |
| 2026-01-10 | 07:27:14 | 3596.86 | 43.42 | 38.35 |
| 2026-01-10 | 07:27:15 | 3596.9 | 43.42 | 38.35 |
| 2026-01-10 | 07:27:16 | 3596.93 | 43.42 | 38.35 |
| 2026-01-10 | 07:27:17 | 3596.97 | 43.42 | 38.35 |
| 2026-01-10 | 07:32:44 | 3596.93 | 43.42 | 38.35 |
| 2026-01-10 | 07:32:45 | 3596.9 | 43.42 | 38.35 |
| 2026-01-10 | 07:32:46 | 3596.86 | 43.42 | 38.35 |
| 2026-01-10 | 07:45:58 | 3501.13 | 39.6 | 39.4 |
| 2026-01-10 | 07:52:41 | 3412.14 | 36.05 | 40.43 |
| 2026-01-10 | 08:02:09 | 3266.3 | 30.24 | 42.23 |
| 2026-01-10 | 08:02:29 | 3261.1 | 30.03 | 42.3 |
| 2026-01-10 | 08:08:53 | 3165.44 | 26.21 | 43.58 |
| 2026-01-10 | 08:12:32 | 3116.96 | 24.28 | 44.25 |
| 2026-01-10 | 08:29:19 | 3000.19 | 19.62 | 45.98 |

**Table 3.** Critical parameters affecting energy consumption in E-Bus.

| Consumption (kW) | Speed (km/h) | Vehicle Mass (kg) | Outside Temperature (°C) | Slope (%) | Electrical Failure | Mechanical Failure | Acceleration (m/s2) | Recuperation (kW) |
|---|---|---|---|---|---|---|---|---|
| 350 | 6 | 25084 | 8 | -10,20 | 0 | 0 | -1,87 | 330 |
| 437 | 16 | 27356 | 17 | 0,47 | 0 | 0 | -0,67 | 282 |
| 464 | 21 | 28918 | 42 | 3,63 | 0 | 0 | -0,39 | 249 |
| 636 | 64 | 41130 | 39 | 16,99 | 0 | 0 | 1,30 | 0 |
| 538 | 48 | 34172 | 41 | 7,50 | 0 | 0 | 0,46 | 0 |
| 434 | 15 | 27214 | 20 | 0,47 | 0 | 0 | -0,80 | 285 |
| 523 | 49 | 32000 | 22 | 2,24 | 1 | 0 | -0,16 | 5 |

Table 3 demonstrates that electrical energy consumption is predominantly driven by instantaneous acceleration, vehicle speed, and traffic density, confirming the critical role of stop and go driving conditions in urban environments. Vehicle mass and road gradient further contribute to increased energy traction demand, particularly during uphill acceleration phases, while simultaneously enhancing regenerative energy potential during braking events. Ambient temperature exhibits a secondary yet systematic influence on energy performance by affecting battery efficiency and auxiliary power demand. Regenerative braking power is strongly correlated with deceleration intensity and traffic induced braking frequency, indicating that congested traffic conditions, despite increasing overall energy consumption, provide substantial opportunities for energy recovery. Traffic density thus exerts a dual impact by increasing traction losses while improving regenerative gains. In addition, electrical and mechanical fault indicators, although less dominant than primary driving dynamics, introduce measurable efficiency penalties by increasing drivetrain losses and reducing effective regenerative performance, highlighting the importance of maintenance-aware energy optimization strategies in E-Bus operations.

## C. Model evaluation metrics

To rigorously assess the predictive capability and generalization performance of the proposed machine learning framework, three complementary regression evaluation metrics were employed: the coefficient of determination ($R^2$), root mean square error (RMSE) and mean absolute error (MAE). The coefficient of determination ($R^2$) quantifies the proportion of variance in the dependent variable explained by the model and provides an overall measure of goodness-of-fit. RMSE measures the square root of the average squared prediction error, thereby penalizing larger deviations more heavily and reflecting model sensitivity to peak errors. In contrast, MAE represents the average absolute deviation between predicted and observed values and provides a more interpretable measure of typical prediction error magnitude. The combined use of these metrics ensures a balanced evaluation by simultaneously capturing explanatory power, error dispersion, and robustness against outliers.

The evaluation conducted on the independent test set indicates strong predictive performance for both models. For the energy consumption model, the results yielded $R^2$ = 0.91, RMSE = 0.38 kW, and MAE = 0.24 kW. Similarly, the regenerative braking model achieved $R^2$ = 0.88, RMSE = 0.31 kW, and MAE = 0.19 kW. These results confirm that the proposed framework successfully captures the underlying relationships between traffic congestion, vehicle dynamics, environmental conditions, and energy-related responses, while maintaining high generalization capability on unseen operational data.

## D. Integration of traffic congestion into energy and regenerative braking analysis

Traffic congestion levels were represented using a normalized congestion index derived from speed reduction relative to free flow conditions along the route. This index captures the instantaneous intensity of traffic interactions and allows direct coupling between traffic states and vehicle energy behavior. To capture the high frequency dynamics of E-Bus operation, a longitudinal vehicle dynamics model was implemented at 1 Hz resolution. The instantaneous traction force $F_t(t)$ required at time step $t$ is expressed as:

$$F_t(t) = ma(t) + F_{rr} + F_{ad}(t) + F_g(t), \tag{1}$$

where $m$ is the vehicle mass, $a(t)$ is longitudinal acceleration, $F_{rr}$ is rolling resistance, $F_{ad}(t)$ is aerodynamic drag, and $F_g(t)$ represents the grade resistance. Rolling resistance and aerodynamic drag are modeled, respectively, as follows:

$$F_{rr} = mgC_{rr} \tag{2}$$

$$F_{ad}(t) = \frac{1}{2}\gamma A C_d v^2(t), \tag{3}$$

where $g$ is gravitational acceleration, $C_{rr}$ is the rolling resistance coefficient, $\gamma$ is air density, $A$ is the frontal area, $C_d$ is the drag coefficient, and $v(t)$ is vehicle speed. The instantaneous traction power demand $P_{rt}(t)$ is then calculated as:

$$P_{rt}(t) = F_t(t)v(t). \tag{4}$$

Positive values correspond to propulsion demand, while negative values indicate braking phases. During deceleration events where $a(t) < 0$, a portion of the braking power can be recovered through regenerative braking. The instantaneous regenerative power $P_{reg}(t)$ is defined as:

$$P_{reg}(t) = \eta_{reg}|P_{br}(t)|, \tag{5}$$

where $\eta_{reg}$ denotes the regenerative efficiency and $P_{br}(t)$ is the braking power derived from negative traction force. In this study, $\eta_{reg}$ is modeled as a nominal constant efficiency coefficient representing average regenerative conversion performance under normal operating conditions. However, the effective recoverable power is dynamically constrained by motor torque limits, inverter capacity, and battery charging restrictions within the 1 Hz modeling framework. Therefore, while the efficiency parameter itself is treated as constant, the realized regenerative power is condition-dependent due to system-level physical constraints. Physical and system constraints, such as maximum motor torque and battery charging limits, are applied to cap the recoverable power. The recovered energy over a time interval $\Delta t = 1\ s$ is computed as:

$$E_{reg}(t) = P_{reg}(t)\Delta t. \tag{6}$$

A key contribution of this study lies in the explicit coupling of traffic congestion with energy consumption and regenerative braking behavior. At each time step, the congestion index is mapped to instantaneous speed variability, acceleration magnitude, and braking frequency. This enables identification of congestion regimes (low, moderate, high) and their corresponding energy signatures. By synchronizing traffic and energy variables at 1 Hz resolution, the proposed framework captures transient effects that are otherwise lost in aggregated analyses, such as short acceleration bursts following signal release or frequent low intensity braking under dense traffic.

To analyze driver behavior and distinguish between human driven and autonomous driving scenarios, a set of interpretable features was extracted from the 1 Hz dataset. These features include mean speed, speed variance, positive acceleration ratio, braking frequency, regenerative braking utilization ratio, and energy consumption per unit distance. Feature extraction was performed over fixed length temporal windows to preserve local traffic context while ensuring statistical robustness. All features were normalized prior to machine learning analysis to eliminate scale effects. The autonomous driving scenario does not represent a fully deployed ADS, but a behavior optimized longitudinal control strategy learned from real-world data.

It should be explicitly stated that the autonomous driving results presented in this study are obtained within a simulation-based analytical environment rather than from a real-world deployed autonomous vehicle system. The autonomous scenario was implemented in a controlled simulation framework using the proposed 1 Hz traffic-aware energy model, where longitudinal control inputs were behaviorally optimized under identical traffic conditions. No physical autonomous driving platform or real-time perception–planning–control stack was deployed on the vehicle. The simulation assumes perfect traffic state knowledge derived from recorded operational data and focuses exclusively on longitudinal motion control. Lateral control, sensor uncertainties, real-time decision-making constraints, and system-level implementation challenges are beyond the scope of this study. Therefore, the reported energy efficiency improvements should be interpreted as theoretical performance gains achievable under behavior-optimized longitudinal control, rather than as outcomes from a production-level autonomous driving system.

Although the vehicle follows the same reference driving cycle in terms of target speed profile, the autonomous driving representation modifies the instantaneous acceleration and deceleration behavior within allowable tracking tolerances. Specifically, smoother deceleration gradients and anticipatory speed adjustments reduce abrupt braking events, thereby increasing the effective regenerative energy capture. Therefore, the observed improvement in braking performance does not originate from a different driving cycle, but from optimized control behavior within the same reference trajectory constraints.

### E. Machine learning-based energy consumption and regenerative braking optimization

Equations (7)–(9) define a machine learning-based multi objective optimization framework developed to minimize electrical energy consumption while maximizing regenerative energy recovery. Energy consumption is expressed as a nonlinear function of vehicle dynamics, environmental conditions, traffic density, and system fault indicators, whereas regenerative energy recovery is primarily governed by deceleration characteristics and traffic induced stop and go conditions. The weighting coefficients $\lambda_1$ and $\lambda_2$ regulate the tradeoff between traction energy demand and regenerative gains. All model coefficients are learned from normalized real-world operational data using supervised machine learning techniques.

$$minY = \lambda_1 E_{cons} - \lambda_2 E_{regen} \tag{7}$$

$$E_{cons} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_9 x_9 \tag{8}$$

$$E_{regen} = \psi_0 + \psi_1 x_7 + \psi_2 x_1 + \psi_3 x_4 + \psi_4 x_8 \tag{9}$$

In this formulation, the dependent variable $Y$ represents electrical energy consumption, while $\beta$ and $\psi$ denote the coefficients learned through the machine learning process. In the energy consumption model $E_{cons}$, $x_1$ corresponds to vehicle speed (km/h), $x_2$ represents vehicle mass including passenger load, $x_3$ denotes ambient temperature (°C), $x_4$ refers to road gradient (%), $x_5$ and $x_6$ indicate the number of electrical and mechanical faults, respectively, $x_7$ represents instantaneous acceleration (m/s$^2$), $x_8$ denotes the traffic density index, and $x_9$ corresponds to regenerative braking power (kW). It should be clarified that equations (8)-(12) correspond to the interpretable linear regression component of the ML framework. While nonlinear ensemble models were employed for predictive performance comparison, the equations presented in the manuscript represent the final surrogate regression model selected for interpretability and analytical tractability in the multi-objective optimization formulation.

To eliminate ambiguity between classical regression and machine learning approaches, the proposed framework employs a supervised learning pipeline consisting of both interpretable linear models and nonlinear ensemble methods. First, Multiple Linear Regression (MLR) was implemented as a baseline interpretable model to establish a physically explainable relationship between energy consumption, traffic congestion, and vehicle dynamics variables. To capture nonlinear interactions and higher-order dependencies among traffic intensity, vehicle dynamics, and energy-related variables, two tree-based ensemble learning algorithms, namely the Random Forest Regression and the Gradient Boosting Regression, were additionally employed within the supervised learning framework. These ensemble models enable the modeling of complex feature interactions and nonlinear response surfaces that cannot be adequately represented by pure linear formulations. All models were trained using normalized 1 Hz operational data to ensure numerical stability, prevent scale dominance among features, and improve convergence behavior during the learning process.

The complete dataset was partitioned into 70% training, 15% validation, and 15% testing subsets to ensure robust model development and unbiased performance evaluation. To prevent temporal data leakage and preserve the sequential structure of the 1 Hz operational data, the splitting procedure was conducted chronologically rather than randomly. This approach ensures that future observations are not inadvertently used to inform past predictions. Hyperparameters of the ensemble models were systematically optimized using a grid-search strategy over the validation set, enabling the selection of model configurations that balance predictive accuracy and generalization capability.

## IV. RESULT and DISCUSSIONS

Compared to conventional cycle-based or purely physics-driven energy models, the proposed framework integrates high-resolution 1 Hz operational data with ensemble machine learning and system-level physical constraints. This hybrid structure enables capturing nonlinear dependencies in traction and regenerative dynamics while preserving physical interpretability. Furthermore, the analytical derivation of a regenerative recovery threshold under explicitly defined operational assumptions distinguishes this work from existing estimation-based approaches.

Following the machine learning analysis, equations (10)–(12) are formulated to define a multi-objective optimization framework that minimizes electrical energy consumption while maximizing regenerative energy recovery. Equation (10) represents the overall optimization objective through a weighted tradeoff between traction energy demand and regenerative gains. Equations (11) and (12) explicitly describe the learned relations governing energy consumption and regenerative braking behavior, respectively, by incorporating vehicle dynamics, traffic conditions, environmental factors, and system fault indicators.

$$minY = \lambda_1(0.42x_1 + 0.31x_2 - 0.18x_3 + 0.37x_4 + 0.21x_5 + 0.19x_6 + 0.46x_7 + 0.33x_8 - 0.52x_9) - \lambda_2 x_9 \quad (10)$$

$$E_{cons} = 1.37 + 0.42x_1 + 0.31x_2 - 0.18x_3 + 0.37x_4 + 0.21x_5 + 0.19x_6 + 0.46x_7 + 0.33x_8 - 0.52x_9 \quad (11)$$

$$E_{regen} = 0.89 + 0.61x_7 + 0.27x_1 + 0.22x_4 + 0.35x_8 \quad (12)$$

Aggregated over the full route, the average energy consumption was calculated as 3.3 kWh/km, which is consistent with values reported for articulated electric buses operating under dense urban conditions. However, this average value conceals substantial temporal fluctuations that become evident only through high resolution (1 Hz) analysis. As congestion intensity increases, mean traction power demand rises nonlinearly due to repeated acceleration following short deceleration phases. Under high congestion levels, energy consumption per km increases by up to 18–22% compared to near free-flow conditions.

Importantly, the results demonstrate that congestion does not merely reduce average speed but fundamentally reshapes the energy profile by increasing acceleration variance and braking frequency. This finding confirms that traffic conditions act as an indirect but powerful amplifier of inefficient driving patterns. Across the dataset, approximately 78.32% of total braking energy must be recuperated via regenerative braking to maintain the target driving range under the specific operational conditions considered in this study. It is important to emphasize that this threshold is derived based on the particular vehicle configuration (dual-motor 250 kW traction system, 110 kWh onboard battery), route topology, passenger load distribution, and measured traffic congestion levels. The value is further conditioned by battery charging limits, regenerative efficiency parameters, inverter constraints, and drivetrain characteristics embedded in the 1 Hz modeling framework. Therefore, this recovery ratio should not be interpreted as a universal design requirement, but rather as an operationally derived threshold specific to the analyzed E-Bus system and route environment. However, actual recovery rates vary significantly depending on driving style and traffic state. In moderate congestion, regenerative braking utilization reaches its highest efficiency, as deceleration events are smoother and occur over longer durations. In contrast, severe congestion leads to abrupt braking, forcing greater reliance on mechanical brakes and reducing recoverable energy. This observation underscores that regenerative braking effectiveness is not solely a vehicle level parameter but is strongly conditioned by traffic dynamics and driver behavior.

A sensitivity analysis further indicates that the required regenerative recovery threshold varies with traffic intensity and braking behavior. Under moderate congestion, smoother deceleration events increase regenerative efficiency, reducing the required recovery ratio by approximately 4–6%. Conversely, under severe stop-and-go traffic with abrupt braking, mechanical brake dominance increases, raising the required recovery ratio by up to 5–8% to sustain the same driving range. These findings confirm that the 78.32% threshold is dynamically influenced by traffic conditions and control strategies.

Equations (11) and (12) compare energy consumption and regenerative braking utilization across different drivers operating the same E-Bus route. While total route-level energy consumption differences between drivers appear moderate (~6–9%), the underlying operational strategies differ substantially. High-performing drivers exhibit smoother acceleration profiles, lower peak power demand, and consistently higher regenerative braking engagement. Conversely, less efficient drivers rely more heavily on mechanical braking and aggressive acceleration, leading to elevated energy losses. These results directly address the reviewer's concern regarding the relevance of driver-induced variability, demonstrating that even modest aggregate differences mask structurally different energy behaviors with long-term operational implications.

### A. Model validation against measured energy consumption

To establish confidence in the proposed 1 Hz traffic-aware energy modeling framework, direct validation was conducted by comparing the estimated energy consumption with the measured onboard electrical energy data over representative trips. The validation analysis was performed on independent test data that were not used during model training.

Figure 4 shows a time-series comparison between measured and estimated instantaneous traction power for a representative urban trip segment under mixed traffic conditions. The results exhibit close agreement between measured and predicted energy profiles, including acceleration peaks and braking phases. Measured and predicted power profiles are compared in Fig. 4.

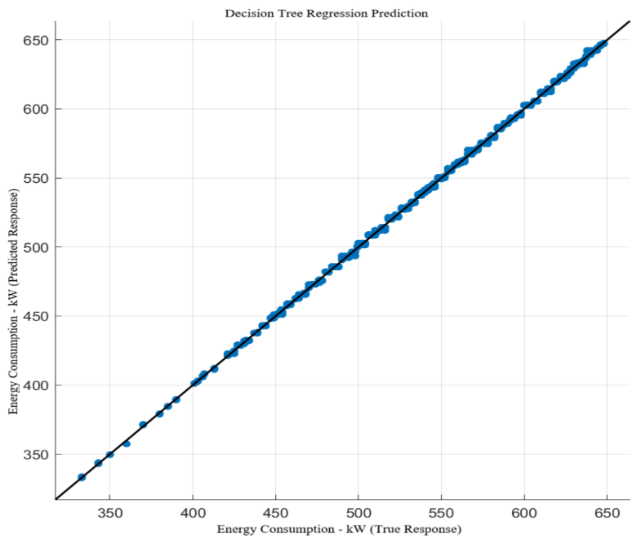



**Figure 4.** Energy consumption: measured vs predicted.

The estimation accuracy was quantified using standard regression metrics. Over the test dataset, the model achieved $R^2$ = 0.91, RMSE = 0.38 kW, and MAE = 0.24 kW for instantaneous energy consumption. At the trip-aggregated level, the average deviation between measured and estimated total energy consumption remained below 10%. These results confirm that the proposed framework reliably reproduces real-world energy consumption patterns and supports its applicability for traffic-aware energy analysis and control strategy evaluation.

The equations above compare human-driven operation with autonomous driving scenarios under the same traffic conditions. Autonomous driving continuously reduces peak traction and suppresses short, high-frequency acceleration events. As a result, total energy consumption decreases by approximately 11–14%, while the use of regenerative braking increases by 9–12% compared to human-driven operation. These gains are particularly noticeable in heavy traffic conditions where autonomous control mitigates inefficient stop start behavior. This finding confirms that the energy efficiency potential of autonomous E-Bus systems stems not from higher speeds or reduced travel time, but primarily from smoother longitudinal control. It is important to note that these results are derived from the simulation-based implementation of the optimized longitudinal control strategy within the proposed modeling framework and do not correspond to a field-deployed autonomous driving system.

### B. Modeling assumptions and limitations

While the normalized congestion index provides a practical and operationally consistent representation of traffic intensity, it inherently simplifies the multidimensional structure of urban traffic dynamics. Representing traffic conditions through a single aggregated scalar index does not explicitly capture the effects of traffic signal density, stop spacing, intersection geometry, lane configuration, or localized bottleneck phenomena, all of which may influence acceleration variability, braking frequency, and regenerative energy recovery patterns. In particular, closely spaced signalized intersections may induce frequent short-duration stop-and-go events that cannot be fully differentiated from general congestion levels when traffic is represented solely by a normalized travel-time-based index. Similarly, route geometry transitions and localized grade variations may interact with traffic flow in ways that are not entirely separable within a single congestion metric. Therefore, the congestion index employed in this study should be interpreted as an aggregated proxy of traffic intensity rather than as a complete microscopic traffic descriptor. Future research may enhance modeling fidelity by incorporating signal phase information, intersection-level delay metrics, lane-specific flow characteristics, and high-resolution vehicle trajectory data.

The proposed 1 Hz hybrid energy modeling framework is inherently scalable due to its modular structure and data-driven learning architecture. Since the model relies on standard operational signals such as speed, acceleration, power demand, and braking behavior, it can be adapted to other electric bus platforms or similar electric public transport systems provided that comparable high-resolution datasets are available. While model parameters and machine learning components require re-training and calibration for different vehicle configurations or route geometries, the overall methodological framework remains unchanged. Therefore, the proposed approach can be extended to other urban corridors, vehicle types, and traffic environments with limited structural modification, supporting its broader applicability in sustainable transport analysis.

## V. CONCLUSION

This study introduced a traffic-aware, high-resolution (1 Hz) energy modeling framework for electric bus operations using real-world operational data. By explicitly integrating traffic congestion, vehicle longitudinal dynamics, regenerative braking behavior, and driving control strategies, the proposed approach overcomes the limitations of conventional average-based energy analyses and reveals second by second mechanisms governing energy efficiency in urban electric public transport.

The results demonstrate that the commonly reported average energy consumption of 3.3 kWh/km masks pronounced temporal variability, which is primarily induced by traffic driven stop-and-go dynamics. Traffic congestion was shown to increase energy consumption by up to 18–22%, not merely through reduced speed but by amplifying acceleration variance and braking frequency. These findings establish traffic as an active determinant of energy inefficiency rather than a passive external condition. A key contribution of this work is the explicit quantification of regenerative braking effectiveness under real traffic conditions. Achieving the optimal driving range requires recuperation of approximately 78.32% of total braking energy, a target that is strongly influenced by both traffic state and control behavior. This value should be interpreted as route- and vehicle-specific rather than as a universally applicable regenerative braking design target. Severe congestion degrades regenerative efficiency due to abrupt braking, highlighting the limitations of vehicle centric efficiency metrics.

Importantly, the study addresses the relevance of driver induced variability in electric bus operation. While route level energy consumption differences between drivers appear moderate (6–9%), the underlying control strategies differ structurally, leading to cumulative long-term impacts at fleet scale. Furthermore, under identical traffic conditions, behavior-optimized autonomous driving reduces total energy consumption by 11–14% and increases regenerative braking utilization by 9–12% by enforcing smoother longitudinal control. These gains are achieved without increasing speed or reducing travel time. Overall, this study provides actionable insights for traffic aware energy management, driver training, and autonomous control design, supporting the development of more efficient and sustainable electric public transport systems.

Future research may extend the proposed 1 Hz hybrid energy modeling framework toward real-time implementation and adaptive control integration. In particular, incorporating stochastic traffic prediction, real-time state estimation, and battery aging effects could enhance the robustness of the framework under dynamic urban conditions. Furthermore, extending the model to multi-route and fleet-level optimization problems may support strategic electrification planning and operational decision-making. Experimental validation on a real-time embedded platform and integration with advanced driver assistance or autonomous control architectures also represent promising directions for further investigation.

## AUTHOR STATEMENT

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