

Article

Sustainable Energy Management in Electric Vehicles Through a Fuzzy Logic-Based Strategy

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Abstract: The purpose of this study was to develop a fuzzy logic controller (FLC)-based energy management strategy for battery electric vehicles that enables them to reduce their energy consumption and carbon emission levels without sacrificing their performance. An electric vehicle model was developed in MATLAB/Simulink using a virtual battery and validated with real-world driving tests to save time and money. An in-depth investigation is conducted on both virtual and real vehicles to confirm the effectiveness of the proposed energy management strategy. This study shows that by using FLC-based energy management, an energy consumption advantage of 9.16% can be achieved while maintaining acceptable performance levels in real-world driving conditions. This advantage results in significant reductions annually: 1044.09 tons of CO₂ emissions, USD 164,770.65 in savings for electric bus lines, and 5079 battery cycles. For European passenger electric vehicles, this corresponds to 405,657.6 tons of CO₂ emissions reduced, USD 64,017,840 saved, and 5.071 battery cycles per vehicle. This strategy not only enhances energy efficiency but also contributes to long-term sustainability in public transportation systems, particularly for electric bus fleets, which play a critical role in urban mobility.

Keywords: battery electric vehicle; energy optimization; fuzzy logic; fleet management; carbon release



Received: 10 October 2024

Revised: 19 December 2024

Accepted: 24 December 2024

Published: 26 December 2024

Citation: Savran, E.; Karpat, E.; Karpat, F. Sustainable Energy Management in Electric Vehicles Through a Fuzzy Logic-Based Strategy. *Sustainability* **2025**, *17*, 89. <https://doi.org/10.3390/su17010089>

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1. Introduction

Electric vehicles (EVs) have emerged as a critical mobility solution, highlighting the growing importance of environmentally friendly transportation in today's world [1]. They stand out with their low carbon emissions compared to internal combustion engine vehicles. They have become an effective tool in combating air pollution and provide a clean and healthy environment for millions of people living in cities [2]. In addition, their high energy efficiency reduces dependence on fossil fuels and enables more sustainable use of energy resources. With the development of battery technology, longer ranges can be reached and a more socially reliable mobility option emerges in urban transportation. The electrification of public transportation also strengthens environmentally friendly and modern mobility. EVs are an important step towards the vision of a cleaner and more livable city in the future. Thanks to technological advances and new optimized vehicle architectures [3], electric vehicles are achieving increased energy efficiency. The potential for reduced energy costs and EV maintenance benefits support the idea that electric fleets are a more economical solution in the long term. Adopting EV fleets leads to achieving environmental goals, developing innovative production methods, and developing green technologies. EV fleets

make transportation more efficient by reducing traffic congestion in urban areas and are an important step towards the sustainable development of cities [4].

EV fleets offer the potential to increase the use of renewable energy sources and reduce energy consumption. They provide significant advantages in terms of sustainability by making energy use more efficient through decentralized energy distribution. Thanks to smart transportation systems and data analytics [5], it is possible to plan routes and charging times most efficiently. Optimal routing enables fleets to operate more efficiently, optimizes energy consumption, and makes urban transportation more sustainable [6]. With their innovations, EV fleets both promote environmentally friendly transportation and contribute to the adaptation of public transportation systems to future energy needs.

Energy consumption optimization in electric vehicles covers many strategies in modern transportation systems. There are various optimization and energy minimization approaches for electric vehicles [7–10]. Optimizations mainly aim to maximize vehicle ranges with efficient energy use. Innovations such as smart charging systems, predictive travel routes, regenerative braking, and battery management systems are used to optimize the energy consumption of electric vehicles and ensure their effective integration into the grid [11]. For example, by preparing a travel plan with a proactive approach, the most efficient route can be created, thus achieving a longer driving range with lower energy consumption. It is possible to achieve more energy-efficient mobility by classifying driver behaviors and designing vehicles according to their characteristics [12]. Grid optimization can be achieved by integrating charging algorithms into route plans and regulating charging times. Thanks to the characteristic feature of electric motors, regenerative braking can provide braking force to the vehicle and feed the battery by generating energy. Battery management systems extend the battery life by optimizing the storage capacity of the battery. Energy consumption optimization makes the use of EVs more attractive and economical, while environmental sustainability is also supported. With the mentioned technological developments, electric vehicles will be able to take a more effective place in public transportation systems and individual use and will make significant contributions to the sustainable transportation of the future.

FLC, which is used to reduce energy consumption in electric vehicles, is a usable tool to minimize carbon emissions by preserving vehicle performance as much as possible. This control system evaluates complex variables to optimize the energy consumption of electric vehicles and ensure their efficient operation [13]. New machine learning methods [14,15], which have been frequently preferred in the literature in recent years, are mostly used in offline studies and have relatively longer processing times. FLC stands out with its ability to intervene instantly in the live system and shorter processing times compared to similar methods. FLC determines the optimum driving parameters by continuously evaluating factors such as vehicle speed, load, route, and battery status [16,17]. This method can also regulate the braking and acceleration processes of the vehicle. In this way, the regenerative braking system is used more effectively and the energy generated during the braking of the vehicle can be accumulated and reused. It also optimizes energy consumption by adapting electric vehicle performance to changing road conditions. It not only reduces energy consumption but also minimizes environmental impacts by reducing carbon emissions. Equipping electric vehicles with FLC contributes to the development of sustainable transportation systems by supporting cleaner and more efficient public transport options in cities of the future [18].

In this study, an energy management strategy based on FLC was developed. A virtual battery EV model was created with the help of MATLAB/Simulink (version R2022a) and helped to test the developed strategy. The developed strategy was transferred to real vehicle traction control software (MATLAB/Simulink R2019b) and real-world driving

effects were studied in terms of consumption and performance. The effect of the achieved consumption reduction was evaluated in terms of consumption, carbon emissions, and cost in an EV fleet.

The contributions of this study to literature are listed below:

- A successful FLC-based energy management system was designed in a single energy source EV architecture;
- The effectiveness of the developed strategy was strengthened by testing it on two different driving behaviors and both virtual and real vehicle models;
- The findings were evaluated and concretized on a real electric bus fleet;
- A comprehensive assessment is made by presenting energy management, cost, and environmental impacts together.

To examine similar studies in literature, research was conducted on the Web of Science, ScienceDirect, and Google Scholar search platforms with keywords such as electric bus fleet, energy consumption, fleet management, and optimization. The studies examined focused on future study topics and determined from which perspectives the current study would fill the gaps in literature. In the studies in the literature, it is emphasized that management strategies in energy consumption of EVs should be suitable for real and different uses, that the optimum energy management system should be determined in single energy source vehicles, that realistic data such as the number of passengers on the route should be taken into account, that the effect of energy consumption on the grid should be investigated and that charging infrastructure support should be well investigated.

Among the valuable studies, Ji et al. [19] study aimed to develop a model for estimating energy consumption in the planning and operation of an electric bus fleet using real-world data from 31 buses in China's Jilin Province and regression models with optimization techniques, showing a reduction of 1.746% when the error rate and boarding and disembarking of passengers are taken into account. Xing et al. [6] introduced a proposed electric bus scheduling optimization model that uses long short-term memory for energy consumption estimation, integrates the results with objectives to minimize fleet size and battery loss, takes constraints into account, and uses the non-dominated sorting genetic algorithm-II. Planning and charging scheme demonstrating an effective reduction in operating costs by optimizing certain battery charge and discharge thresholds. Doulgeris et al. [20] discussed a pilot program in Athens, Greece, led by the Athens Urban Transport Organization, focusing on the evaluation of energy consumption in battery electric buses operating on existing bus lines and using a combined experimental and simulation approach that takes into account various factors. Ambient temperature and air conditioning use reveal a daily energy consumption range of 96 kWh/km to 220 kWh/km, and the impact of air conditioning on energy consumption is emphasized. Yin et al. [21] regulated the power distribution between battery and ultracapacitor using an adaptive Fuzzy Logic Controller. They determined the optimum parameters for energy management by analyzing various driving cycles (city, highway, etc.). The system performance was compared with other energy management strategies using various driving cycles (JC08 and HWFET). The developed strategy achieved the best comprehensive performance among the methods that do not require driving cycle information. The fluctuations were greatly reduced. Using an ultracapacitor as an energy buffer minimized the state-of-charge differences. Afonso [22] compared conventional diesel, parallel hybrid, and battery electric buses on the island of Tenerife and found that battery electric buses show a 70% reduction in energy consumption, but the carbon intensity of the island's electricity grid reduces their potential to reduce energy consumption. In contrast, parallel hybrid buses offer the biggest benefit, with a 38% reduction compared to their conventional diesel counterparts. Hjelkrem et al. [23] presented a new energy model for battery electric buses, developed from established

longitudinal dynamic models and low-frequency event-based data, that can accurately predict energy consumption with minimal input requirements for practical application in bus route planning; it also includes a comprehensive utility system model validated on 3266 Ebus trips in China and Norway, demonstrating the effectiveness of this model in predicting trip-by-trip energy consumption. Basma et al. [24] proposed a framework based on comprehensive energy needs assessment using an energy model that takes into account different types of bus services, and highlighted the critical role of appropriate battery size for battery electric buses worldwide; findings show sensitivity to service types associated with intercity buses requiring the largest battery size (320–680 kWh), and practical insights from a case study in Paris reveal that urban bus batteries are often oversized to accommodate rare extreme cold weather conditions. Mišanović et al. [25] investigated the factors affecting the electricity consumption in real operating conditions of electric buses running on a bus line in Belgrade, covering various seasonal and daily operating periods, and its results form the basis for planning line operations, analyzing energy efficiency and optimizing operating conditions. Li et al. [26] presented a new energy-optimal speed control model for connected electric buses that use advanced technology to consider factors such as passenger load and seamless passage through intersections. Formulated as a mixed integer linear program, the model exhibits high computational efficiency and achieves a significant 40% reduction in energy consumption in numerical experiments. The precise analysis also confirms the model's robust performance against changes in vehicle mass and prediction errors in passenger load, revealing its potential to significantly increase energy efficiency in urban transport networks.

2. Materials and Methods

In this study, an FLC-based energy management strategy was developed and tested in single-source battery electric vehicle architecture. In the development process of the energy management strategy, a virtual vehicle model was created in MATLAB/Simulink (version R2022a) and validated with real-world driving data. The first developed strategy was integrated into the virtual vehicle model. Energy consumption reduction and dynamic performance were examined. Based on the remarkable results obtained in the virtual vehicle model, the developed energy management strategies were applied to the real vehicle traction control software. The optimum energy management strategy was defined according to the success criteria. The energy consumption reduction obtained in real driving was evaluated on the energy consumption of an electric bus fleet and a passenger electric vehicle. In addition, the effect of the consumption reduction on carbon emissions was estimated. The general flow of this study is explained in Figure 1.

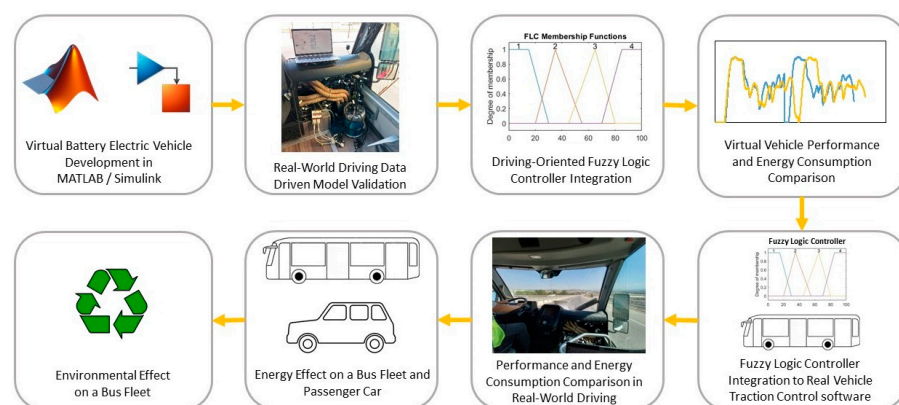


Figure 1. Graphical flow of the methodology.

2.1. Virtual Battery EV Model

Since the effect of this study on the real vehicle would take a long time to be seen and would be costly, a virtual vehicle model was created. The virtual vehicle model works with 3 inputs: speed, slope, and mass and gives the vehicle's performance and consumption outputs. During this process, the virtual driver, which shows realistic behavior, decides on the required power and torque value according to the speed target and drives the system. The subsystems include motor efficiency, dynamic resistances, and battery calculations. The operations of the virtual EV model are shown in Figure 2.

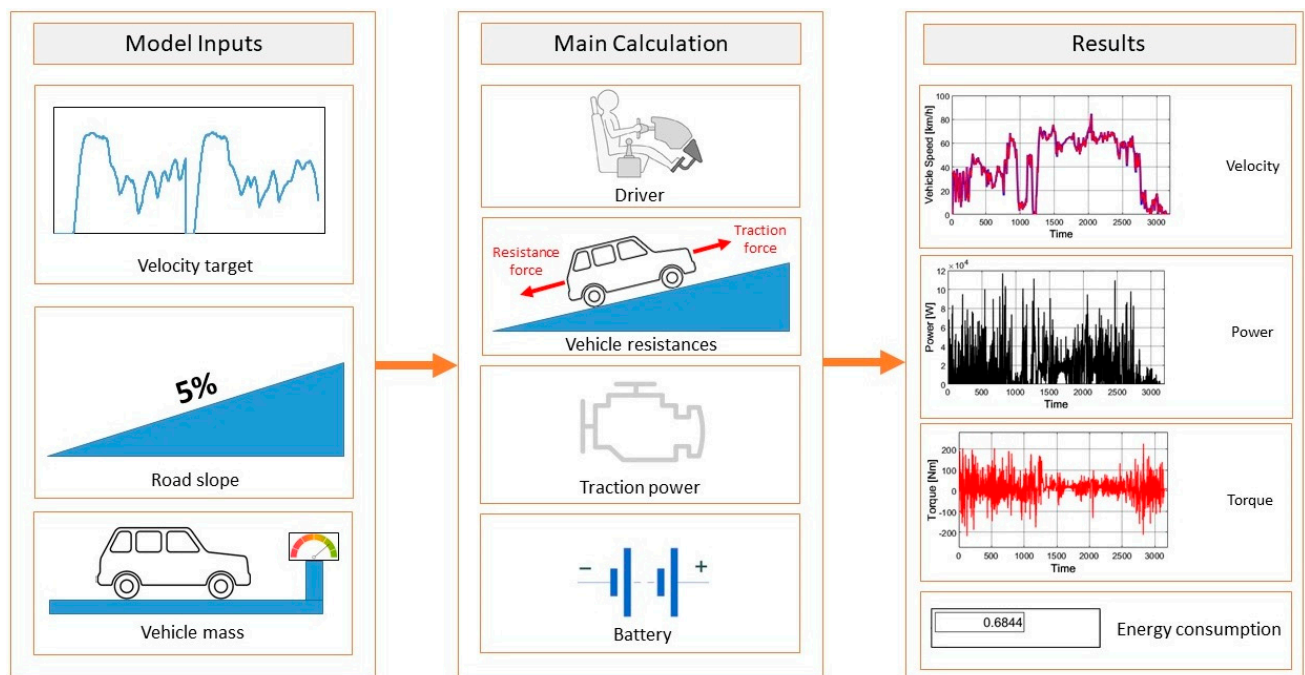


Figure 2. Schematic of the virtual EV model.

The virtual electric vehicle model, which was constructed according to the basic dynamic calculations in the reference [8], is in Figure 3.

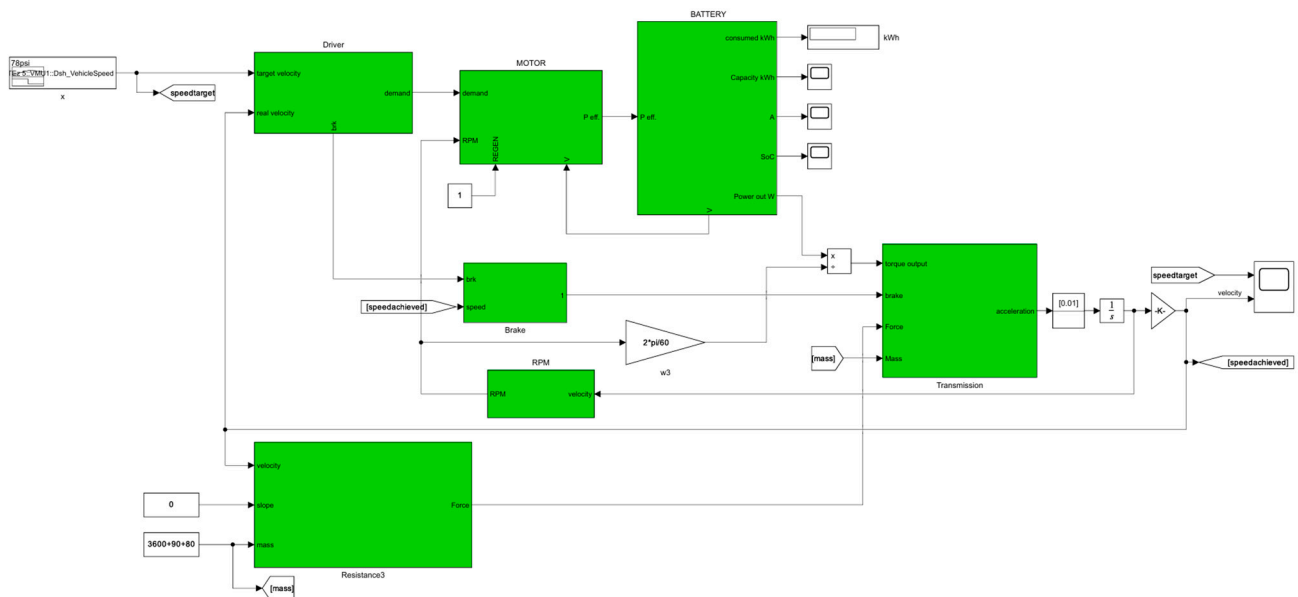


Figure 3. Visualization of the virtual vehicle model in MATLAB/Simulink.

2.2. Virtual Electric Vehicle Model Validation

To see the FLC activity, a virtual vehicle model was created in MATLAB/Simulink (version R2022a). To save time and cost, the accuracy of the virtual vehicle model should be verified. Verification can be performed with another virtual system whose accuracy is known or with real-world vehicle driving behavior. In this study, the virtual vehicle model designed was verified with data obtained from real-world driving of a real battery electric vehicle under certain conditions. The technical specifications of the battery electric vehicle driven in the real world are shared in Table 1.

Table 1. Vehicle characteristics.

Property	Value	Unit
Vehicle length	6–8	
Motor type	PMSM	
Maximum motor power	100–200	kW
Maximum motor torque	200–300	Nm
Battery type	Li-ion	
Battery capacity	70–150	kWh
Passenger capacity	18–35	
Vehicle full load	3000–5000	kg
Transmission ratio	12–20	
Frontal area	5–6	m ²
Drag coefficient	0.6	
Rolling coefficient	0.0082	

Figure 4 includes the route for the virtual model validation test and a moment from the real-world drive. The drive was performed in 0.421 km on a windless, paved, known gradient road with light traffic and a temperature of approximately 15 °C. Before the drive, tire pressures were checked and equalized. The battery SoC value was checked to ensure that there would be no power loss. During the drive, energy-consuming systems (air conditioning, entertainment system, audible warning, etc.) were turned off, except for the traction system and driver information system.

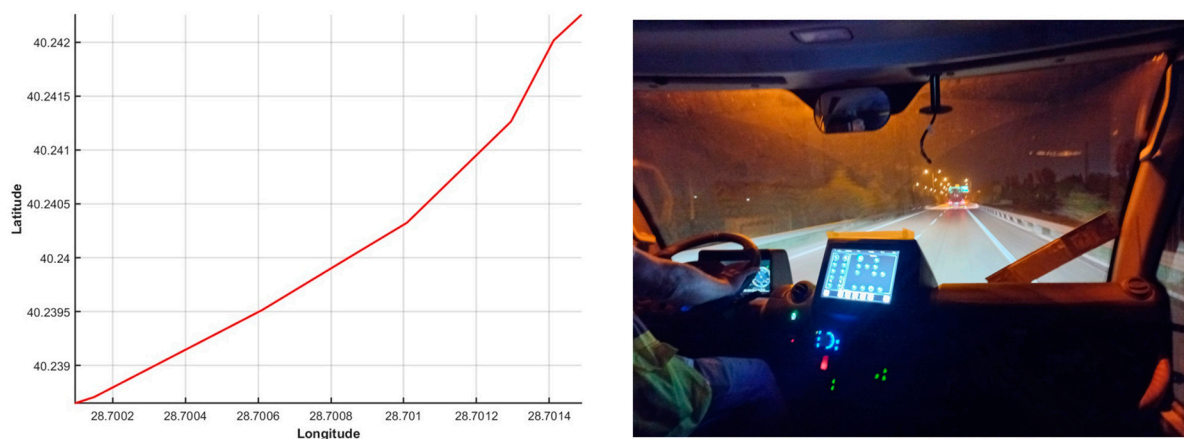


Figure 4. Virtual vehicle model validation test procedure: real-world driving route (left), a moment of test driving (right).

During the drives, the vehicle was connected to the VECTOR device via the On-board Diagnostics (OBD-II) output, and the driving data were recorded in .BLF format with the CANalyzer 15 software. Then, it was converted into a meaningful form with the help of the CAN database (DBC) file, and a .CSV file was obtained. In the created driving data file, speed, motor speed (RPM), motor torque, motor power, and motor control unit

voltage-current values were extracted, and total energy consumption was calculated as kilowatt-hours. The speed graph, slope value, and vehicle mass obtained in real driving were given as input to the virtual vehicle model, and vehicle speed, motor speed, motor torque, and motor power values were obtained. The obtained virtual values were compared with the data obtained in real driving.

Figure 5 shows the real-world driving results, and the values obtained from the virtual vehicle model to validate the virtual vehicle model. The comparison graphs of vehicle speed, engine speed, engine torque, and engine power show a strong correlation between the virtual and real vehicle dynamics. As a result of the validation performed with real-world driving, the real consumption was measured as 0.1154 kWh, while the energy consumption of the virtual vehicle under the same conditions was 0.1145 kWh.

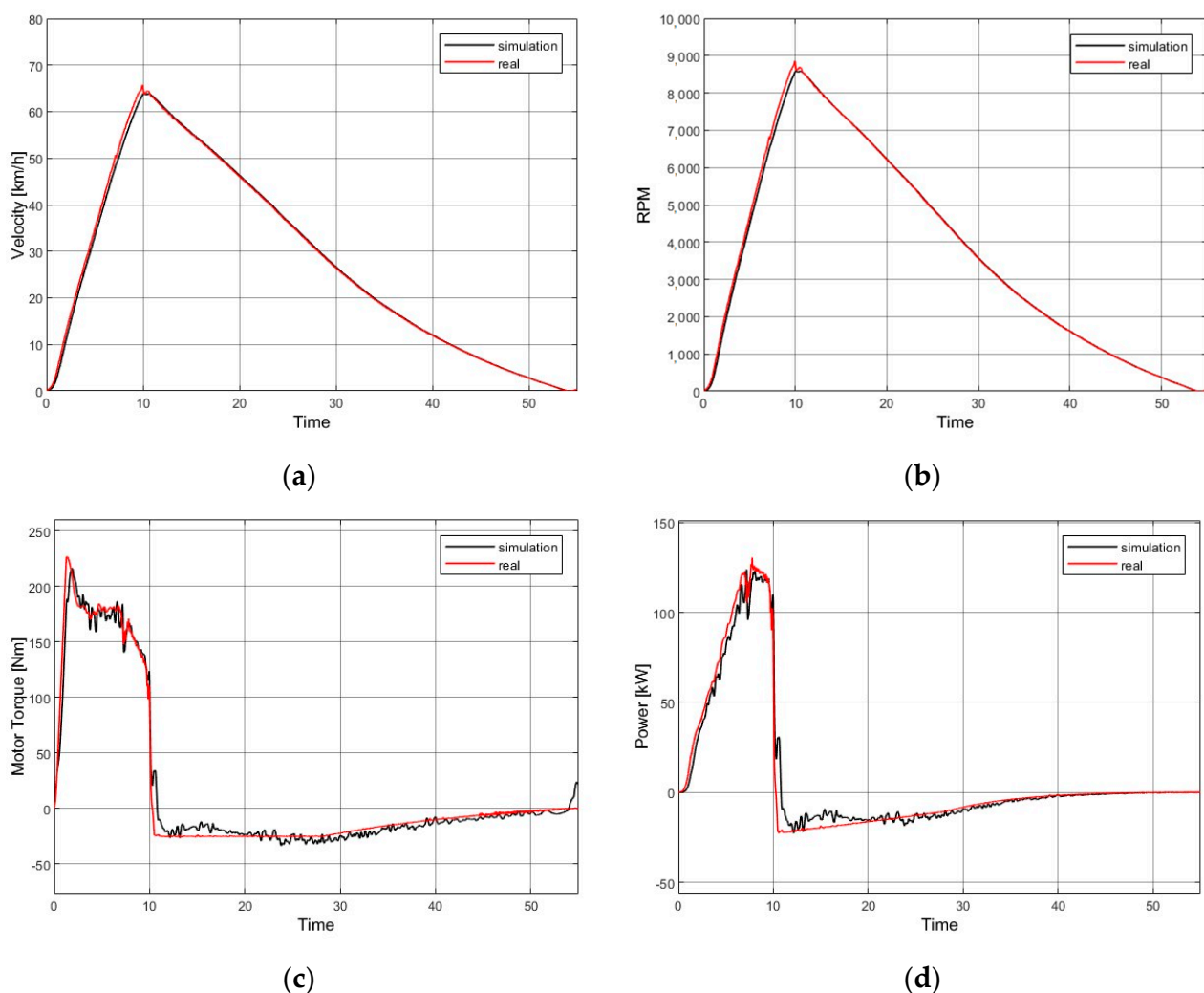


Figure 5. Data-driven validation results: (a) vehicle speed, (b) motor speed, (c) motor torque, (d) motor power.

2.3. FLC Integration to Virtual Vehicle Model

The driving-oriented vehicle energy management strategy includes Type-I FLC. Type I FLC is widely used in many engineering and control applications. More complex systems such as Type-II or Type-III can be preferred when the level of uncertainty and fuzziness needs to be addressed in more detail. The developed strategy places the virtual battery in the motor subsystem of the EV model. The output of the controller is the motor torque limit according to the vehicle speed, pedal ratio, and SoC values. If the torque value determined according to the RPM and demand ratio in the motor subsystem does not exceed the limit

determined by the FLC, the torque requested by the system is allowed; otherwise, the torque is transferred to the system at the decision value given by the controller. The virtual vehicle model with FLC integration is shown in Figure 6.

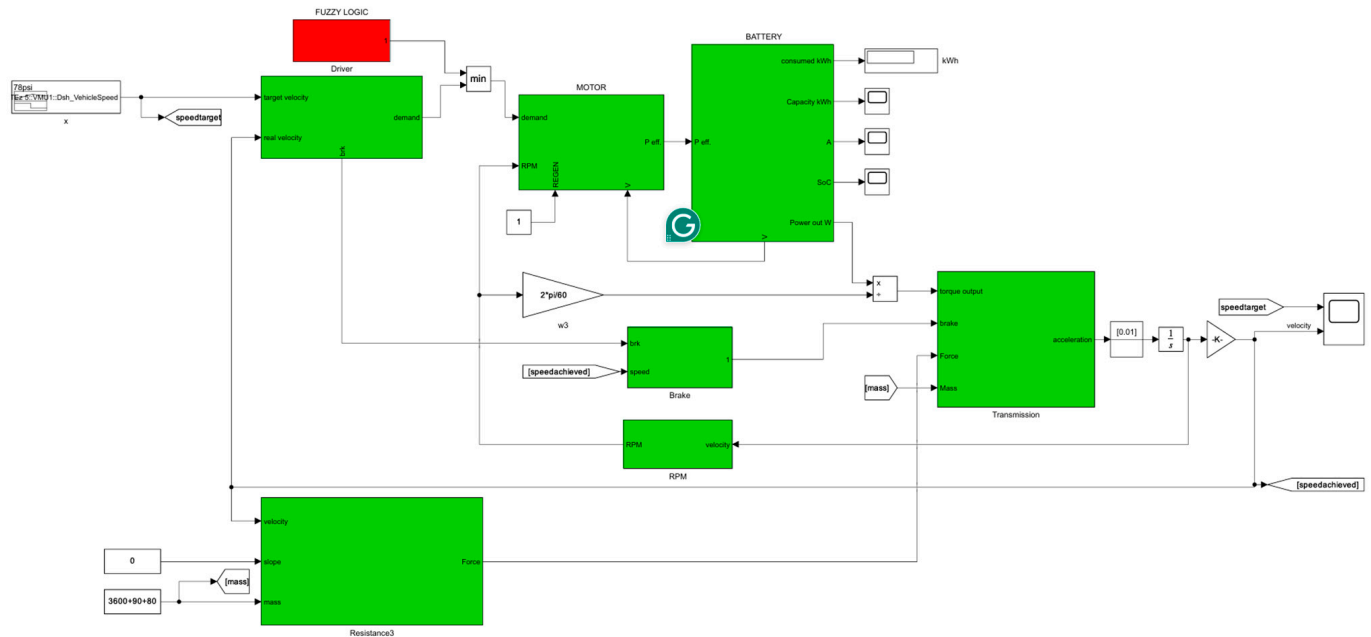


Figure 6. FLC integrated virtual vehicle model.

The output to be obtained in response to the input selected in the FLC is expressed by the center of gravity of the sum of the groups it is included in. The center of gravity method emerges as the “best case” decision in the situation we are faced with. This study used the MATLAB (version R2022a) Fuzzy toolbox for FLC in energy management. Mamdani interface system was preferred. While the inputs vary between vehicle speed 0–105, pedal ratio 0–100, and SoC 0–100, velocity 4, pedal 4, and SoC 4 triangular-type membership functions are created. In the rule viewer, an “and” connection is placed between the input parameters. On the output side, the pedal value varies between 0 and 100 and is divided into 4 triangular membership functions. Details of the specified inputs and outputs are shared in Figure 7.

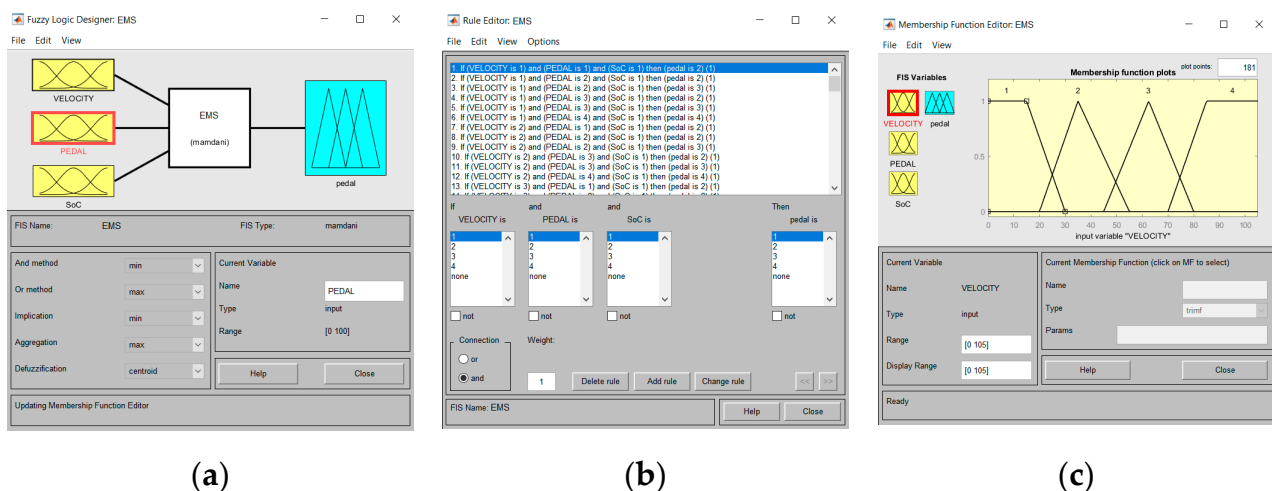


Figure 7. Cont.

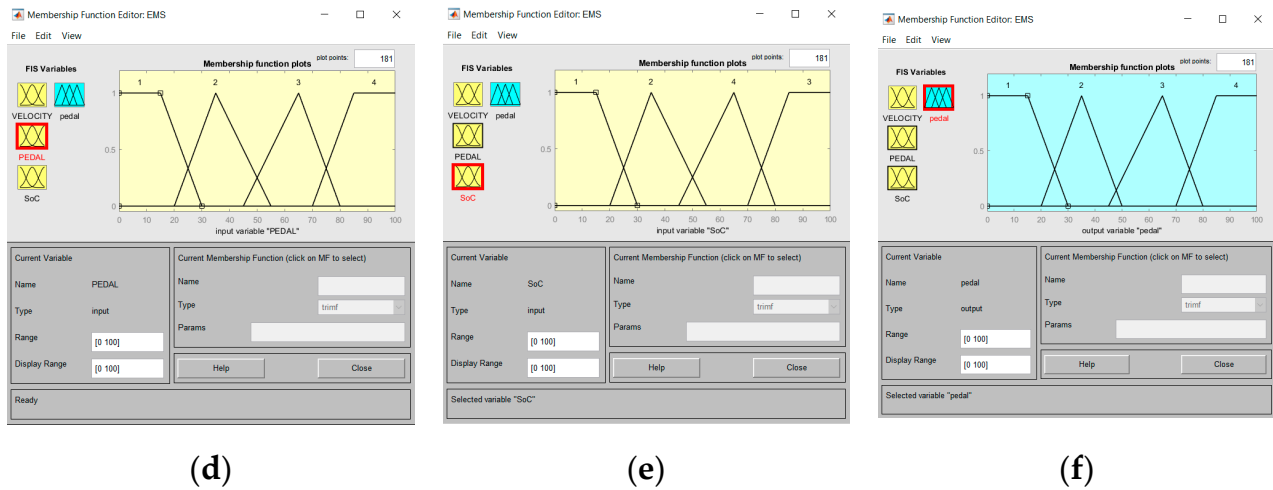


Figure 7. FLC tool interfaces: (a) main page, (b) ruler viewer, (c) velocity membership functions, (d) pedal ratio membership functions, (e) SoC membership functions, (f) torque membership functions.

Two different FLCs were designed to comparatively examine the effects on electric vehicle dynamic performance and energy consumption. The systems, whose membership function intervals and decision-making rules are quite similar, are named FLC-V1 and FLC-V2. The membership functions of FLC-V1 and FLC-V2 are in Figure 8. The target of the designed energy management system is to reduce energy consumption without sacrificing vehicle dynamic performance. In this respect, the success criterion of the energy management system has been determined as a minimum of 5% reduction in energy consumption and a maximum of 5% reduction in dynamic performance loss. The performance evaluation is calculated based on the speed difference that can be achieved at the end of a full-throttle start on a 7% slope in the first 13 s of the ride.

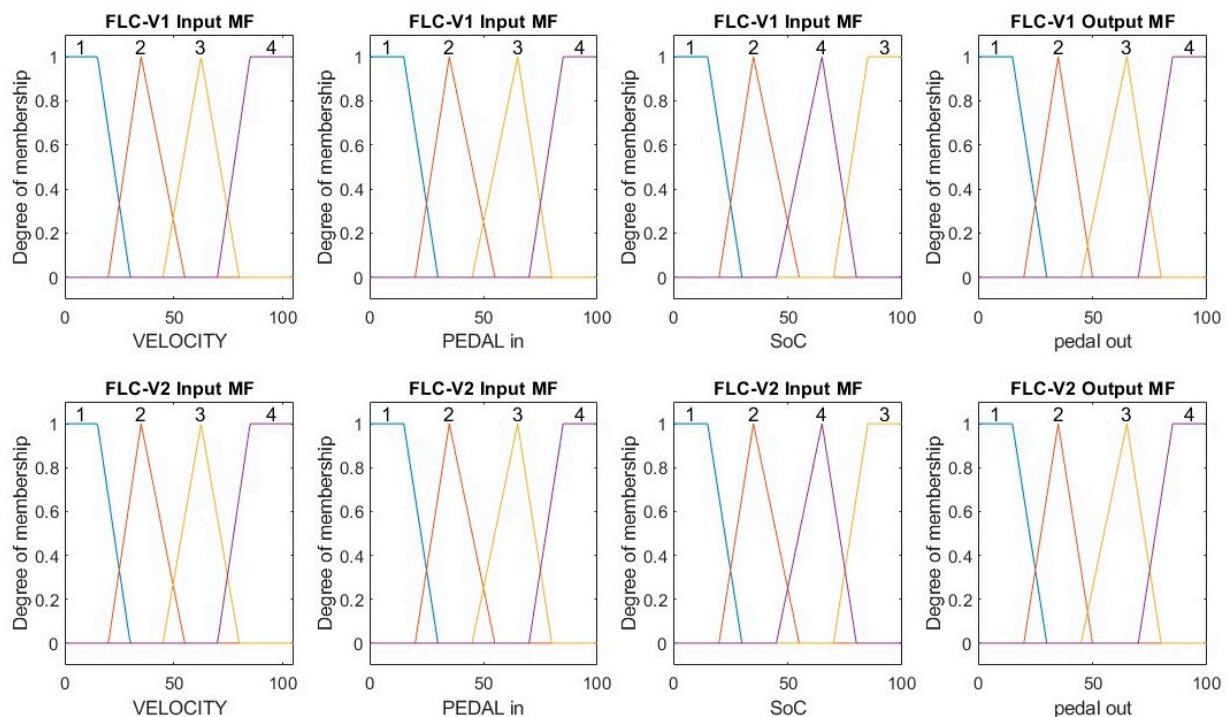


Figure 8. Membership functions of FLC-V1 and FLC-V2.

2.3.1. The First Trial of FLC

The first trial of the embedded energy management strategy with FLC-V1 was carried out using the virtual vehicle model. This phase is the preliminary step for the real implementation of the energy management strategy. The conditions determined for the verification test were defined and run on the FLC-V1 integrated virtual vehicle model. To examine the effect of the developed strategy, acceleration, and consumption differences were considered performance criteria. According to the results obtained in the first trial, the real test phase started in the second trial.

2.3.2. The Second Trial of FLC

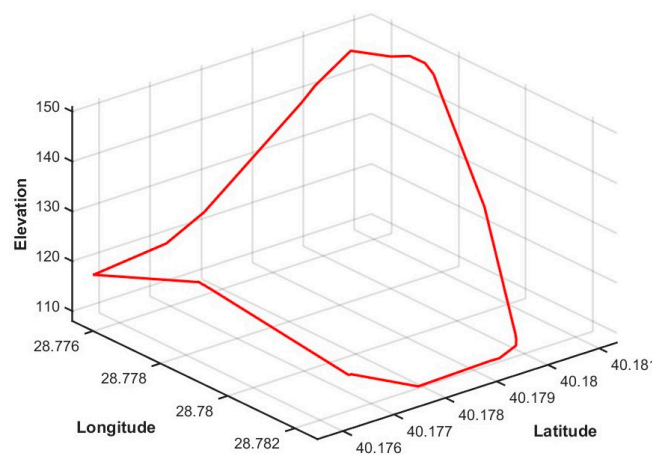
Following the positive results seen in the integration of FLC-V1 into the virtual vehicle model, the developed strategy was integrated into the real vehicle traction control software. Since the real traction vehicle control software supports the MATLAB/Simulink base, the control set created in the virtual vehicle model was successfully transferred to the vehicle software side as it is. In addition, the control strategy was made parametric for driving safety and could be turned off instantly when necessary. To see the integrated energy management strategy in real driving, the 2.125 km test route whose coordinates are shared in Figure 9 was determined. The vehicle ran 2 laps each with the normal and FLC-V1 and FLC-V2 integrated software (MATLAB/Simulink R2019b) on the specified route.



(a)



(b)



(c)

Figure 9. Real-world driving test procedure: (a) FLC-V1 integrated driving moment, (b) FLC-V2 integrated driving moment, (c) driving data obtained from driving route.

2.4. Energy Assessment on a Bus Fleet

The effectiveness of the FLC-supported energy management system has been demonstrated with both real and simulation-based approaches. A comprehensive evaluation of the effective meaning of the achieved consumption reduction was requested. Battery electric bus fleets, with relatively high energy consumption, are a suitable example for this subject. The energy consumption value of a 12 m battery electric bus suitable for urban use is 1.3 kWh/km on average [27]. Considering that 13.7 million kilometers are covered annually in urban transportation [28], 17,810,000 kWh of energy is consumed annually. The savings that can be obtained by applying the developed strategy to a 10-vehicle electric bus fleet were evaluated.

The steps to be taken in the concept of sustainable mobility require serious studies and are of high importance. In this context, the positive change to be made in public transportation fleets with high carbon emissions in reducing environmental impacts will provide great economic and environmental impacts. The electrification of urban public transport vehicles significantly reduces carbon emissions. For example, it is reported that the electrification of buses on two lines in Luxembourg has achieved an equivalent carbon capture of 1.161 tons per year over a distance of 1.1 million kilometers [28]. There are many valuable studies in the literature [29] that include carbon assessment of public vehicles both during the production process and during their use. In addition to the willingness of countries to reduce carbon emissions, the fact that they also have official obligations further increases the seriousness of the issue. The Paris Agreement [30], signed in 2015, covers issues related to climate change mitigation, adaptation, and financing and shares tasks with countries on an annual basis. Apart from this, countries need to control their carbon emissions by various methods within the scope of sustainability for the period when the carbon tax [31] issue is on the agenda. For these reasons, energy consumption and environmental impact assessment are presented together to see the wide-ranging effect of the energy gain obtained in this study.

3. Results

FLC has advantages in handling uncertainty and applying expert knowledge, but it has limitations compared to machine learning (ML) methods that can autonomously learn from large datasets and adapt to more complex, dynamic conditions. Based on general knowledge, ML can detect a pattern in a dataset without prior definition and interpret similar conditions in the future. Rule-based control systems have a structure that implements response conditions created by an expert who knows the system's behavior. FLC offers more flexibility and adaptability than rule-based management systems, allowing it to adjust EV performance under changing driving conditions without high computational costs. However, in applications that require high precision or autonomous optimization, ML approaches can offer superior performance. In this study, the FLC-based energy management strategy was examined in two stages, virtual and real. In the first stage, a positive consumption change was observed in the trial conducted on the virtual vehicle model. Thereupon, the second stage, which was the real trial, was passed. The developed strategy was integrated into the vehicle traction control software and real-world driving was performed. To concretize the resulting consumption reduction rate and better understand its effect, a line including electric buses was considered. The consumption reduction was evaluated in terms of battery life, carbon emissions, and cost.

3.1. FLC Integrated First Trial Results

The first trial of the developed strategy was carried out on the virtual vehicle model. According to the numerical effect results to be seen in the first stage, the transition to the real application was made. In the trial carried out on the virtual vehicle model, the consumption value was 0.1118 kWh. In the virtual vehicle verification test, the FLC—V1 supported energy management strategy provided a consumption reduction of 2.3% according to the 0.1145 kWh consumption reference. On the other hand, there was a slight decrease in the final speed value. As seen in the speed graph in Figure 10, while the final speed was 64 km/h, it decreased to around 62 km/h with the developed strategy. In this respect, there was a decrease of 3.125% in the vehicle speed performance.

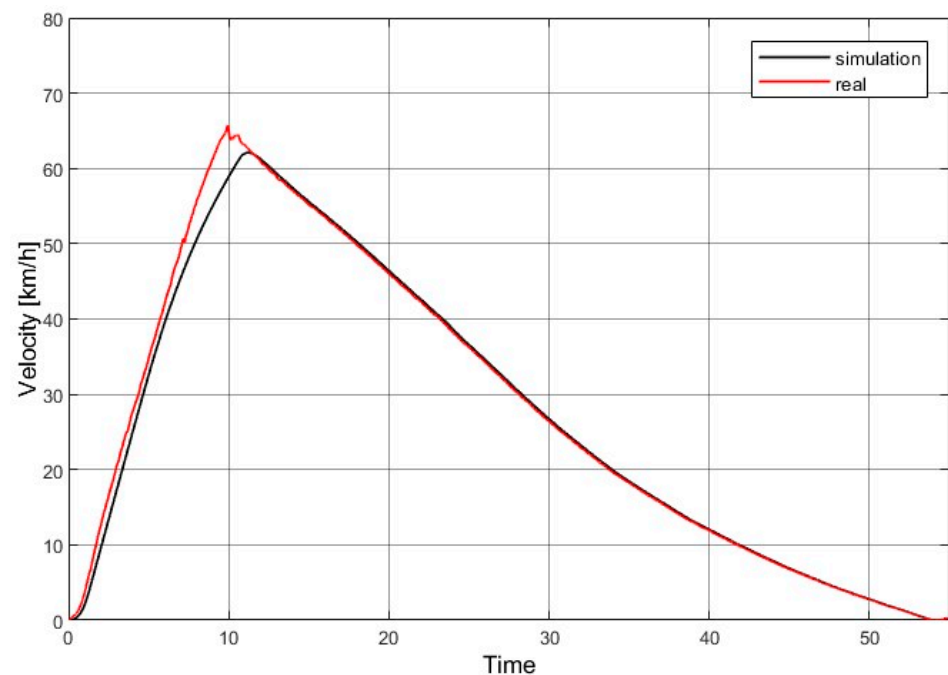


Figure 10. FLC—V1 driven first trial speed graph.

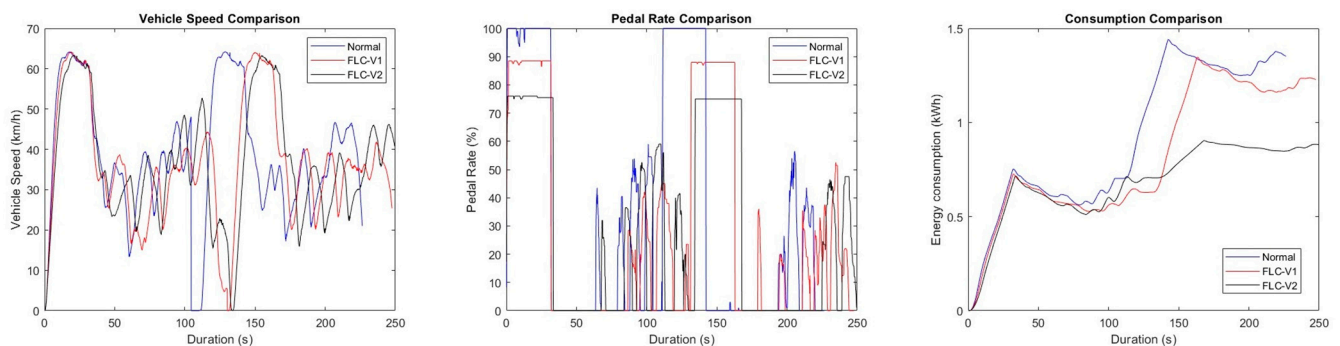
3.2. FLC Integrated Second Trial Results

In the first trial conducted on the virtual vehicle model, a transition was made to the second trial to see the positive change in energy consumption in the real vehicle. At this stage, the energy management strategy developed with MATLAB/Simulink support was integrated into the vehicle traction control system and a real-world drive was performed. In the real-world route, there is a 7% slope in the first 13.1 s of driving. A net performance evaluation was carried out when the vehicle started at full throttle on the slope. In real-world driving, 1.352 kWh of energy was consumed with the energy management strategy off, while 1.228 kWh of energy was consumed with the FLC—V1 and 0.883 kWh of energy was consumed with the FLC—V2. Accordingly, energy consumption decrease was achieved at 9.16% and 34.7% with FLC-V1 and FLC-V2, respectively. The acceleration time from 0 km/h to 60 km/h was measured as 10.5 s with the normal vehicle traction control software, 12.3 s with the FLC—V1, and 16.7 s with FLC—V2. The methodology comparison results are shared in Table 2.

Table 2. Methodology comparison.

Feature	FLC-V1	FLC-V2
Energy consumption reduction (%)	9.16%	34.69%
Performance loss (%)	2.69%	10.16%
Parameter optimization	Manuel	Manuel
Application method	Simulation and real-time	Real-time
Method complexity	low	low
Membership function types	trapmf	trapmf
Input 1 (Velocity) and membership function range	0–15–30	0–15–30
	20–35–55	20–35–55
	45–62.5–80	45–62.5–80
	70–85–105	70–85–105
Input 2 (Pedal rate) and membership function range	0–15–30	0–15–30
	20–35–55	20–35–55
	45–62.5–80	45–65–80
	70–85–100	70–80–100
Input 3 (SoC) and membership function range	0–15–30	0–15–30
	20–35–55	20–35–55
	45–62.5–80	45–62–80
	70–85–100	70–83–100
Output (Maximum pedal rate) and membership function range	0–15–30	0–15–30
	20–35–50	20–32–50
	45–65–80	45–62.5–80
	70–85–100	70–83–100

Figure 11 shows the speed, pedal rate, and total energy consumption with and without the FLC integration. According to the results seen in the graphs in Figure 11, FLC-V1 provided a 9.16% reduction in energy consumption, while it showed a 2.69% performance decrease in full-throttle take-off on the ramp. FLC-V2 provided a 34.69% reduction in energy consumption, while it showed a 10.16% decrease in dynamic performance evaluation. With these results, it was seen that FLC-V1 met both dynamic performance and energy reduction success criteria.

**Figure 11.** Cont.

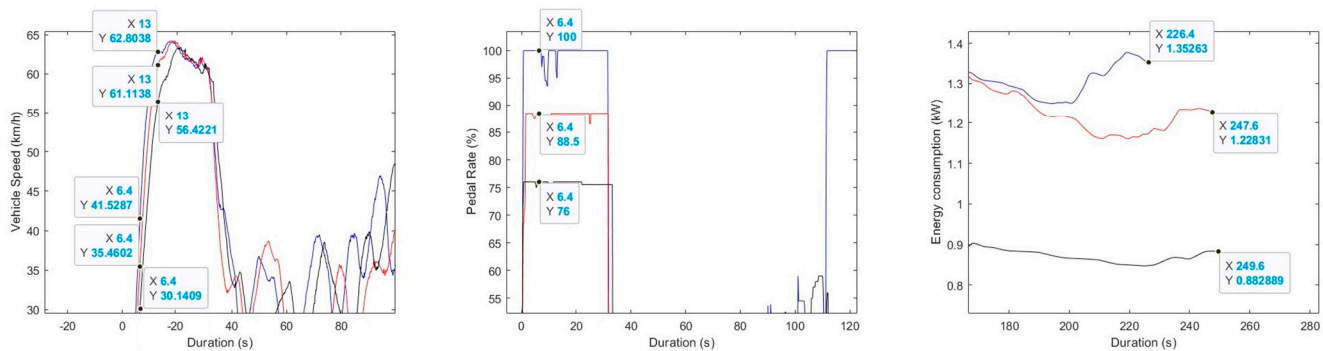


Figure 11. Vehicle performance comparison with FLC.

3.3. Energy Assessment on a Bus Fleet Results

The FLC-based energy management strategy was integrated into the vehicle traction software and a 9.16% energy consumption improvement was achieved in real-world driving. To better understand the effect of this consumption reduction, an evaluation was made of a fleet of 12 m electric buses. The potential for a 12 m urban battery electric bus to decrease the reference energy consumption value from 1.3 kWh/km to 1.181 kWh/km has emerged. With this strategy, it is possible to reduce the annual total energy consumption value from 17,810,000 kWh [28] to 16,178,604 kWh on a line with a distance of 13.7 million kilometers per year. With this approach, the annual energy saving on the specified line alone will be 1,631,396 kWh. For a typical urban electric bus, considering a battery capacity of 400 kWh [20], it is possible to reduce the battery cycle from 44,525 to 40,446. This will create the opportunity for longer battery life. Globally, 35.12% of electricity production comes from coal [32]. Besides the dominance of coal in electricity generation, it has extremely negative effects on human health. Studies have shown that in addition to its negative effects on the lungs, immune system, heart, and brain, it also causes DNA damage [33]. Coal was the focal point in the energy assessment since coal has the highest share in energy production and its negative effects on carbon emission and human health. It was stated that the carbon emission for energy obtained from coal was 640 g/kWh [34]. According to this value, it is possible to reduce carbon emission value by 1044.09 tons with the reduction in energy consumption achieved thanks to the FLC-based strategy. Considering the cost of generating electricity from coal as USD 0.053/kWh, the energy consumption reduction with the [35] FLC-based energy management strategy also brings an annual saving of USD 86,463.9. This strategy could result in an additional annual saving of USD 78,306.75 in carbon taxes, assuming a carbon price of USD 75/ton by 2030 [36].

There is also significant potential for passenger EVs, which play an important role in transportation. Considering that the real-world energy consumption of a passenger EV is 0.207 kWh/km [37], the annual driving range is 13,344 km [38], the number of EVs in Europe is 2,500,000 [39], the average battery capacity of passenger EVs is 50 kWh [40], the total energy savings on an annual basis will be 633,840,000 kWh, the cost savings from energy consumption reduction will be USD 33,593,520, the cost savings from the carbon emission reduction will be USD 30,424,320 (regarding the 405,657.6-ton carbon saving), and the battery cycle reduction for a passenger EV will be 5.071.

There is also a cost-benefit in return for the advantages of the developed energy management strategy. In this study, since the software infrastructure of the vehicle in which the strategy was developed is based on MATLAB and Simulink, the license costs of Mathworks products [41] were considered in the cost assessment. The cost of standard and perpetual MATLAB licenses used in developing this strategy was estimated at USD 2450, the FLC Toolbox license at USD 1400, and Simulink at USD 1250. The total license

cost stands out at USD 5100. When the hourly wage of a vehicle software developer is USD 50/h, and the development of the strategy and its integration into the vehicle software is completed in 2 weeks, the approximate cost will be USD 6000. In case the FLC requires improvements and updates over time, a budget of approximately USD 3000 can be allocated. According to these estimates, the total development and implementation cost will be USD 14,100. Considering the savings from energy consumption reduction and carbon tax on an annual basis, the strategy cost will be amortized within 1 year.

The successes presented by this study also bring some difficulties. There is a processor in the ECU that exchanges information during dynamic operation in the electronic control unit (ECU) of the traction control system. The management strategy integrated into the software increases the processing load and therefore the CPU-load rate increases. When the CPU load reaches a critical level, the ECU resets itself for 300 ms, and vehicle control is lost. On the other hand, there is a CANbus in vehicles that facilitates component communication and control. CANbus also has a certain data load capacity. If the capacity limits are approached, even critical signals that should be present may be suppressed. This may cause the communication between the vehicle components to be interrupted and the vehicle to be out of control. The processing frequency of the fuzzy-logic-based management strategy should be well-optimized for the healthy operation of the vehicle control system. Since the developed management strategy technically intervenes in the driver's acceleration demand or directly the engine torque demand and restricts it according to the place, there will likely be a decrease in the vehicle's dynamic performance. Figures 10 and 11 in the manuscript clearly show the acceleration performance in the first trial conducted in the virtual environment. As can be seen, there is a slight decrease in the vehicle's final speed. At this point, it is necessary to consider how much energy is gained in return for an acceptable performance loss. In the results of this study, the decrease in energy consumption in return for the performance loss not felt by the driver met the authors' expectations. Several software platforms and tools are required to integrate the developed strategy into the vehicle traction control system.

4. Conclusions

In this study, an FLC-based energy management strategy was developed for a battery electric vehicle. Thanks to the developed strategy, energy consumption in real-world driving was reduced by 9.16%. In terms of time and cost savings, the first trial was carried out by integrating the FLC-based strategy into the virtual battery electric vehicle model created in MATLAB/Simulink. Upon the positive results in the consumption value, the strategy was integrated into the real vehicle, and real driving tests were carried out. To evaluate the large-scale effect of the consumption reduction obtained, 12 m battery electric bus fleets were examined in terms of energy consumption and environmental impact. The inferences made based on the results obtained in this study are as follows:

- The virtual vehicle model is quite successful in predicting the real vehicle behavior;
- The FLC-based strategy provides serious advantages in energy consumption with acceptable performance loss;
- The FLC-based strategy provides effective results in single-energy source systems as well as hybrid vehicles;
- Battery cycle decrease can be achieved with the help of an optimal energy management strategy;
- An annual saving potential has emerged at USD 164,770.65 on an electric bus line, USD 64,017,840 on overall European EVs;
- Annual carbon emission reduction potential as 1044.09 tons for an electric bus line and 405,657.6 tons for European EVs.

Author Contributions: Conceptualization, E.S. and E.K.; methodology, E.S.; software, E.S.; validation, E.S.; investigation, E.S.; data curation, E.S.; writing—original draft preparation, E.S.; writing—review and editing, E.S. and E.K.; visualization, E.S.; supervision, F.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by TUBITAK, project number 119C154.

Data Availability Statement: Data are available and can be provided upon request.

Acknowledgments: Authors present their appreciation to TUBITAK (project code: 119C154).

Conflicts of Interest: The authors declare no conflicts of interest.

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