Research Article

Optimizing Energy Efficiency for Connected and Autonomous Electric Vehicles in the Context of Vehicle-Traffic Interaction

Shermila Crespo[1]

1. Anna University, India

The operational efficiency of connected and automated electric vehicles (CAEVs) is significantly impacted by the interplay between vehicle dynamics and traffic conditions. This study presents an energy-conscious optimization (ECO) approach aimed at enhancing the energy efficiency of CAEVs. This is achieved by addressing the dynamic constraints of the traffic environment and the vehicle's powertrain limitations within a unified framework. To develop the ECO approach, a novel bias deep compensative estimator is introduced to determine the parameters of the vehicle dynamics model. Utilizing these identified parameters, the traffic environment's constraints are translated into corresponding powertrain constraints for CAEVs. In the pursuit of optimal energy efficiency while adhering to powertrain limitations, a fresh velocity-torque coordinate system is established to normalize the constraints. Additionally, an iterative neighborhood search algorithm is proposed to systematically explore the coordinate system and identify the optimal efficiency point. With this newfound optimal efficiency point, a torque tracking control strategy is formulated. This strategy serves to guide the electric powertrain, ensuring its operation within the high-efficiency region. Real-world experiments are conducted to validate the effectiveness of the proposed approach, with a direct comparison against two prevailing state-of-the-art methods.

Correspondence: papers@team.qeios.com — Qeios will forward to the authors

1. Introduction

Connected and autonomous electric vehicles (CAEVs) have garnered significant attention due to their potential to revolutionize transportation systems, offering benefits such as reduced emissions and increased traffic safety [1]. However, the efficient operation of CAEVs is challenged by the intricate interplay between vehicle dynamics and traffic conditions. This study explores recent advancements in optimizing energy efficiency for CAEVs within the context of vehicle-traffic interaction [2]. The complex interaction between CAEVs and traffic environments is a crucial factor affecting their energy efficiency. Researchers have recognized the need to develop optimization strategies that consider both the vehicle's operational requirements and the dynamic constraints imposed by varying traffic conditions. Studies underscore the significance of modeling this vehicle-traffic nexus accurately [3].

Several control strategies have been proposed to optimize energy efficiency while accounting for traffic-induced constraints. A predictive control approach that anticipates traffic conditions and adapts vehicle speed and power usage accordingly [4]. This strategy effectively reduces energy consumption by exploiting traffic patterns. The reinforcement learning-based controller enables CAEVs to make energy-efficient decisions in real-time traffic scenarios. To integrate traffic dynamics into energy optimization, researchers have focused on translating traffic-related constraints into powertrain constraints. To map traffic density variations onto speed profiles, enabling CAEVs to adjust their power usage proactively [5]. This approach ensures optimal energy consumption while adhering to traffic-induced limitations. Accurate parameter estimation is vital for effective energy optimization. A deep learning-based estimator accurately identifies vehicle dynamics parameters [6]. This estimator enhances the accuracy of energy optimization models, resulting in improved energy efficiency for CAEVs.

Creating a standardized coordinate system for translating traffic constraints into powertrain limitations has shown promise in optimizing energy efficiency. The velocity-torque coordinate system aids in characterizing the relationship between vehicle speed and power consumption. This approach facilitates the development of energy-efficient control strategies.

Iterative search algorithms have gained attention for identifying optimal efficiency points within the powertrain's constraints [7]. The neighborhood iterative searching algorithm efficiently explores the velocity-torque coordinate system. This method ensures thorough exploration of the solution space and leads to enhanced energy efficiency [8]. To validate the proposed optimization strategies, real-world experiments and comparative studies have been conducted. They executed experiments on a CAEV test

doi.org/10.32388/WOM15I.3

bed, demonstrating the efficacy of their energy-conscious control strategy in various traffic scenarios. Comparative studies provided insights into the advantages of the presented methods over existing state-of-the-art approaches.

2. Illustration of Vehicle Kinematics and Powertrain Configuration

During intelligent obstacle avoidance maneuvers in vehicles, maintaining the same speed could compromise safety and ride comfort, particularly when executing high-speed steering to avoid obstacles [9]. Ensuring vehicle safety through speed planning is paramount for a comfortable driving experience. Thus, speed planning aligned with local path planning becomes necessary [10]. Coordinated control in both horizontal and vertical dimensions allows vehicles to smoothly navigate around obstacles.

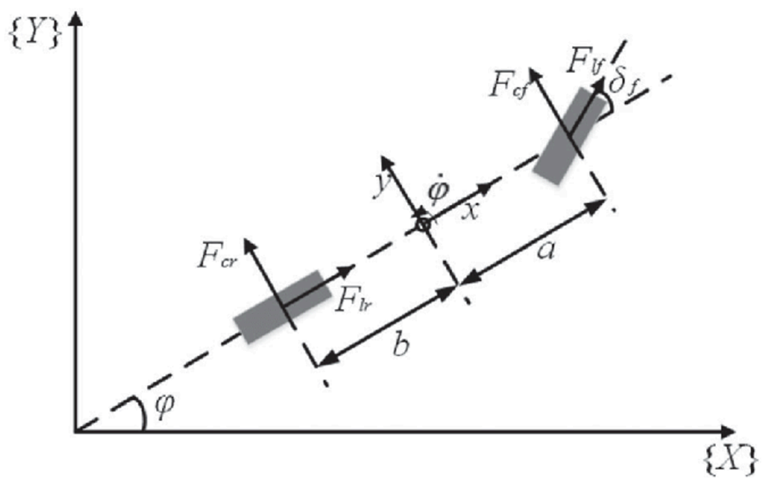

Figure 1. Vehicle Kinematics

Utilizing the obstacle avoidance path depicted in Figure 1 and considering the obstacle's position and speed relative to the vehicle, a reference speed control model is formulated as follows:

$$V\_ref = \{\lambda * d * v'\_t + v'^2 / (2 * a\_max) + d\_0 * v', \text{ if } d \leq \rho\_0 * v', \rho\_0 * v', \text{ if } d > \rho\_0 * v'\} \quad (1)$$

Where:

- d represents the relative distance between the vehicle and the obstacle.
- d_0 signifies the predefined safety distance.

doi.org/10.32388/W0M15I.3

- v' is the vehicle's speed before obstacle avoidance.
- a_{max} denotes the maximum deceleration capacity of the vehicle.
- λ is a constant coefficient.
- t stands for the duration from the initiation of braking until the vehicle comes to a halt.
- ρ_0 defines the obstacle's influence range.

Equation (1) illustrates that, upon entering the obstacle's influence range, the vehicle's speed diminishes proportionally to the distance from the obstacle. As the vehicle circumvents the obstacle, its speed adjusts based on the gap between the vehicle and the obstacle. Once the vehicle exits the obstacle's influence range, the control model no longer dictates the speed, allowing the vehicle to continue accelerating due to the gravitational force exerted by the reference trajectory."

3. Problem Formulation of Eco

Within the framework of Connected and Autonomous Electric Vehicles (CAEVs), the autonomous driving system comprises three distinct layers: the perception layer, the decision-making layer, and the control layer [11]. The perception layer acquires information from the traffic environment, the decision-making layer determines the permissible driving zone and vehicle velocity, while the control layer fine-tunes and optimizes the steering angle and speed [12]. The CAEV's status is influenced by the traffic conditions, encompassing elements such as pedestrians, infrastructure, surrounding vehicles, and road conditions. Onboard sensors and the Internet of Vehicles (IoV) technology facilitate the acquisition of traffic environment information. Given the specific focus of this article on enhancing CAEV energy efficiency, the discussion does not delve into the details of perceiving traffic environment information.

In terms of longitudinal motion, the dynamic constraints posed by the traffic environment manifest through the vehicle's longitudinal attributes—namely, speed and acceleration [13]. These constraints are governed by considerations of driving safety, comfort, and energy efficiency, leading to the formulation:

$$v_{min}(k) \leq v(k) \leq v_{max}(k) \quad (2)$$

$$a_{min}(k) \leq a(k) \leq a_{max}(k) \quad (3)$$

In the context of CAEVs, these dynamic traffic constraints heavily influence motor operation efficiency, yet their impact on battery and power electronics efficiency is comparatively minor [14]. Consequently, this article predominantly concentrates on optimizing motor operation efficiency. According to the

doi.org/10.32388/W0M15I.3

vehicle dynamics and powertrain models expounded in this Section, the motor's angular velocity correlates with vehicle speed and acceleration, and this relationship is represented as:

$\omega(k) = g\_\omega(V(k), A(k))$ (4)

Here, g_ω represents an implicit function with respect to V(k) and A(k). Leveraging Equations (2) and (3), the motor torque is articulated as:

$Tm(k) = mr(a(k) - uf(k)) / (V(K))$

$= mra(k) / (V(K)) + mg\mu(k)\ r \cos\theta(k) / (V(K)) + mgr \sin\theta(k) / (V(K)) + 0.5\rho ACdrv\text{^}2(k) / (V(K))$ (5)

It's noteworthy that motor torque hinges on factors like rolling resistance coefficient, vehicle speed, and acceleration. This relationship can be expressed as:

$TM(K) \propto G\_T(V(K), A(K), \mu\ (K))$ (6)

Where G_T is an implicit function pertaining to v(k), a(k), and $\mu(k)$. Consequently, the dynamic traffic constraints can be translated to motor operation constraints, embodying a mapping correlation.

4. Strategy for Monitoring and Managing Torque

A torque tracking control strategy is a critical aspect of connected and automated electric vehicles (CAEVs) to ensure efficient and safe operation [15]. This strategy involves managing and controlling the torque produced by the electric motors in response to various driving conditions and control inputs. In a connected and automated electric vehicle, torque tracking control is integrated with the vehicle's communication and sensing systems [16]. These vehicles are equipped with sensors, cameras, lidar, radar, and other technologies to gather real-time data about the vehicle's surroundings, road conditions, traffic, and more [17]. This data is used to make informed decisions about torque distribution. Torque tracking involves maintaining a desired torque output from the electric motor to achieve the desired vehicle performance, efficiency, and safety. This can include managing torque between different wheels or axles in an all-wheel-drive system, dynamically adjusting torque for regenerative braking, and distributing torque between front and rear motors for optimal traction control [18].

Monitoring and managing torque in Commercial Autonomous Electric Vehicles (CAEVs) is a multifaceted strategy critical to their overall performance, energy efficiency, and safety [19]. In this era of sustainable mobility, the precise control of torque can significantly impact a CAEV's range, battery life, and overall drivability. A comprehensive approach to torque management in CAEVs involves various components and

doi.org/10.32388/WOM15I.3

considerations, all geared towards achieving optimal performance while maintaining efficiency. To begin with, the implementation of real-time torque sensors throughout the vehicle's drivetrain is essential [20]. These sensors, strategically placed at key points such as the motor, wheels, and axles, continuously monitor torque levels. By providing instant feedback, they enable the vehicle's control systems to make real-time adjustments based on actual operating conditions [21]. This ensures that the CAEV operates within safe and efficient torque ranges, preventing potential damage to the drivetrain components and improving overall reliability.

The data collected by these sensors is then transmitted to an onboard control system or a central vehicle management unit. Here, advanced data processing algorithms come into play [22]. These algorithms analyze the torque data, looking for patterns and anomalies. By identifying unusual torque fluctuations or irregularities, the CAEV's control systems can respond proactively, mitigating potential issues before they escalate. This predictive maintenance approach helps in reducing downtime and maintenance costs, a critical consideration for commercial vehicle operators [23]. One of the key aspects of torque management in CAEVs involves the development of torque management profiles. These profiles are tailored to various driving conditions and scenarios [24]. For instance, during acceleration, the torque profile can be adjusted to provide maximum power, ensuring swift and responsive acceleration. Conversely, during deceleration or downhill driving, regenerative braking systems come into play. These systems capture excess kinetic energy and convert it into electrical energy, which is then fed back into the battery. By controlling the regenerative braking torque based on the vehicle's speed and the state of charge of the battery, CAEVs can maximize energy recovery and extend their range [25].

The strategy for monitoring and managing torque in CAEVs is a multifaceted approach that integrates real-time sensors, data processing algorithms, customized torque profiles, regenerative braking systems, and dynamic torque allocation [26]. This holistic approach aims to strike a balance between performance and efficiency while ensuring the vehicle's safety and reliability. As CAEV technology continues to evolve, torque management will play an increasingly crucial role in realizing the full potential of electric commercial vehicles, reducing operational costs, and contributing to a sustainable and efficient transportation ecosystem [27].

4.1. Control Strategies

Various control strategies can be employed for torque tracking in CAEVs.

Model-Based Control: Using mathematical models of the vehicle dynamics, electric motors, and powertrain components to calculate and adjust torque distribution.

Feedback Control: Utilizing feedback from sensors and actuators to continuously adjust torque output based on real-time data.

Predictive Control: Anticipating upcoming driving conditions and adjusting torque proactively to optimize performance and efficiency.

We have examined the interrelationship between the constraints imposed by the traffic environment and those of the vehicle powertrain. Furthermore, we have outlined a technique to determine the constraints on the motor torque. In the context of direct current (dc) motors, the motor's angular velocity is essentially determined by the motor torque. This relationship in the frequency domain can be represented as follows:

Angular Velocity ($\omega(s)$) = Motor Torque (Tm(s)) - Load Torque (TL(s)) Js + B (7)

Here, TL represents the load torque, J signifies the moment of inertia, B denotes the viscous friction constant, and 's' is indicative of the Laplace transform. Consequently, achieving Energy-Conscious Operation for Connected and Automated Electric Vehicles (CAEVs) is feasible through the control of the motor torque to ensure its operation aligns with the desired value.

By leveraging the algorithm, it is possible to explore the optimal value within the V-T coordinate system. This exploration facilitates the determination of the desired motor torque:

Desired Motor Torque (Tm-des(k)) = Maximum Motor Torque (Tm-max) × Ti(k) (8)

In the context of a dc motor, manipulation of the motor torque is accomplished through the supplied voltage (U). The frequency-domain relationship between the intended supplied voltage (Udes) and the targeted motor torque (Tm-des) can be expressed as follows:

Intended Supplied Voltage (Udes(s)) = (Ls + R) Tm-des(s) Kt+ Ke$\omega(s)$ (9)

Where L corresponds to armature inductance, R signifies armature resistance, Ke stands for the back electromotive force constant, and Kt represents the torque constant. Consequently, the disparity between the intended supplied voltage (Udes) and the actual supplied voltage (U) can be formulated as:

Voltage Discrepancy (ΔU(s)) = Udes(s) - U(s) (10)

Typically, regulation of the supplied voltage is executed through pulse-width modulation (PWM) inverters. The transfer function of the PWM inverter in the frequency domain can be described as:

doi.org/10.32388/W0M15I.3

Transfer Function of PWM Inverter (GPWM(s)) = Ks1 + Ts*s (11)

The above expressions capture the core concepts within the discussed sections.

Parameters	(mm) / Degree
Caster Angle	21°
Normal Trial	71°
Mechanical Trial	72mm
Vertical Displacement of Wheel Centre	2 mm
Tire Size	15 inches

Table 1. Configured Parameters and Test CAEV Specifications

5. Results of Eco

In order to verify the energy-saving effectiveness of the ECO strategy, a practical comparative experiment is carried out within a real-world traffic scenario.

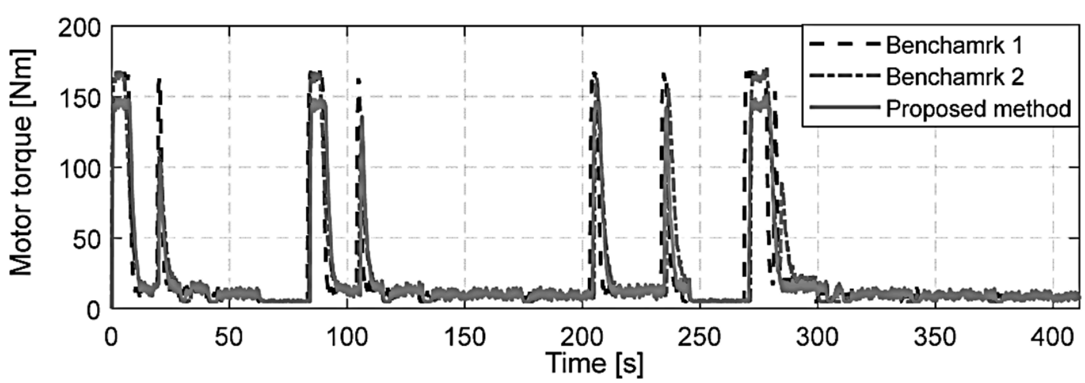

Figure 2. Speed of the vehicle and powertrain performance – motor torque

The depicted Figure 2 illustrates the speed of the vehicle along the test road. Upon a thorough examination of the motor torque as presented in Figure 2, a noteworthy observation emerges: the peak

doi.org/10.32388/W0M15I.3

values achieved through the proposed method are notably lower compared to those attained through the benchmarked methods. This discrepancy signifies that the maximum output power achieved via the proposed method remains less than that achieved through the benchmarked approaches. In order to showcase the operational efficiency of the motor, a comprehensive efficiency Mapping (MAP) is established. This mapping is constructed by considering the motor torque, the motor's angular velocity, and the computed efficiency.

The ECO strategy consists of three key phases:

Traffic-to-Powertrain Constraint Conversion: The first step involves translating the constraints from the traffic environment into the vehicle's powertrain. Specifically, this process focuses on mapping the limitations related to motor angular velocity and motor torque.

Optimal Efficiency Search Using V-T Coordinate System and NIS Algorithm: The second phase of the strategy revolves around seeking optimal efficiency by employing a V-T (Velocity-Torque) coordinate system in conjunction with the NIS (Nexus Interaction Strategy) algorithm.

Efficiency Enhancement of the Electric Motor via Torque Tracking Control: The final step is dedicated to optimizing the electric motor's efficiency by implementing precise torque tracking control.

6. Conclusion

This article introduces an ECO (Energy-Conscious Optimization) strategy aimed at enhancing the energy efficiency of Electric Commercial Autonomous Electric Vehicles. This research confirms that optimizing the powertrain while taking into account the interplay between the vehicle and traffic conditions is an effective means of enhancing the energy efficiency of CAEVs. This optimization is achieved by aligning the constraints of the traffic environment with those of the powertrain, specifically focusing on constraints related to motor angular velocity and motor torque. The research demonstrates that the proposed ECO strategy significantly improves the operational efficiency of electric powertrains in CAEVs. In comparison to state-of-the-art methods, the proposed strategy results in a more extensive distribution of operational points within the high-efficiency region. Consequently, the comprehensive efficiency achieved with the proposed approach surpasses that attained through benchmarked methods. This study has presented a fresh approach for increasing the driving range of Commercial Autonomous Electric Vehicles. The energy consumption findings reveal that the proposed ECO strategy achieves a relatively better energy-saving rate in comparison to existing state-of-the-art methods. Consequently, this strategy offers substantial savings in CAEV battery energy.

Statements and Declarations

Data Availability

The experimental data supporting the findings of this study are available from the corresponding author upon reasonable request.

Author Contributions

Conceptualization, S.C.; Methodology, S.C.; Software, S.C.; Validation, S.C.; Formal Analysis, S.C.; Investigation, S.C.; Resources, S.C.; Data Curation, S.C.; Writing – Original Draft Preparation, S.C.; Writing – Review & Editing, S.C.; Visualization, S.C.; Supervision, S.C.; Project Administration, S.C.

Code Availability

The code developed for the algorithms presented in this study is available from the corresponding author upon reasonable request.

References

1. ^*Zhang Y, Chen J, You T, Zhang Y, Liu Z, Du C (2024). "Energy-Aware Optimization of Connected and Automated Electric Vehicles Considering Vehicle-Traffic Nexus." IEEE Transactions on Industrial Electronics.* ***71****(1): 282–293. doi:10.1109/TIE.2023.3245204.*
2. ^*Chung J (2013). "A proposal for the IEEE EV LiB cell safety standard." 2013 International Conference on Connected Vehicles and Expo (ICCVE). Las Vegas, NV, USA. 437–442. doi:10.1109/ICCVE.2013.6799832.*
3. ^*Wang B, Dehghanian P, Wang S, Mitolo M (2019). "Electrical Safety Considerations in Large-Scale Electric Vehicle Charging Stations." IEEE Transactions on Industry Applications.* ***55****(6):6603–6612. doi:10.1109/TIA.2019.2936474.*
4. ^*Jacob AT, Lindsay NM (2022). "Designing EV Harness Using Autocad Electrical." 2022 8th International Conference on Smart Structures and Systems (ICSSS). Chennai, India. 1–4.*
5. ^*Han J, Sciarretta A, Ojeda LL, De Nunzio G, Thibault L (2018). "Safe- and Eco-Driving Control for Connected and Automated Electric Vehicles Using Analytical State-Constrained Optimal Solution." IEEE Transaction*

s on Intelligent Vehicles. ***3****(2):163–172. doi:*10.1109/TIV.2018.2804162.

6. ^*Xu G, Xu K, Zheng C, Zahid T (2016). "Optimal Operation Point Detection Based on Force Transmitting Behavior for Wheel Slip Prevention of Electric Vehicles." IEEE Transactions on Intelligent Transportation Systems.* ***17****(2):481–490. doi:*10.1109/TITS.2015.2480116.
7. ^*Dabbaghjamanesh M, Kavousi-Fard A, Zhang J (2021). "Stochastic Modeling and Integration of Plug-In Hybrid Electric Vehicles in Reconfigurable Microgrids With Deep Learning-Based Forecasting." IEEE Transactions on Intelligent Transportation Systems.* ***22****(7):4394–4403. doi:*10.1109/TITS.2020.2973532.
8. ^*Sarma DVK, Lindsay NM (2023). "Structural Design and Harnessing for Electric vehicle Review." 2023 9th International Conference on Electrical Energy Systems (ICEES). Chennai, India. 107–111.*
9. ^*Chan C, Rubesh, Pant (2023). "Analyzing Gender based Two-Wheeler Electric Vehicle Riding in Relation to Accidents." International Journal Of Novel Research In Engineering Sciences (IJNRES). 23–25.*
10. ^*Akinapalli PK, Pawar DS, Dia H (2023). "Classification of motorized two-wheeler riders' acceleration and deceleration behavior through short-term naturalistic riding study." Transportation Research Part F: Traffic Psychology and Behaviour.* ***96****:92–110.*
11. ^*N ML, Rao AE, Kalyan MP (2022). "Real-Time Object Detection with Tensorflow Model Using Edge Computing Architecture." 2022 8th International Conference on Smart Structures and Systems (ICSSS). Chennai, India. 01–04.*
12. ^*Chau KT, Chan CC, Liu C (2008). "Overview of Permanent-Magnet Brushless Drives for Electric and Hybrid Electric Vehicles." IEEE Transactions on Industrial Electronics.* ***55****(6):2246–2257. doi:*10.1109/TIE.2008.918403.
13. ^*Guo Y, Xiong J, Xu S, Su W (2016). "Two-Stage Economic Operation of Microgrid-Like Electric Vehicle Parking Deck." IEEE Transactions on Smart Grid.* ***7****(3):1703–1712. doi:*10.1109/TSG.2015.2424912.
14. ^*Alaoui C, Salameh ZM (2005). "A novel thermal management for electric and hybrid vehicles." IEEE Transactions on Vehicular Technology.* ***54****(2):468–476. doi:*10.1109/TVT.2004.842444.
15. ^*Lindsay NM, Emimal M (2023). "Longevity of Electric Vehicle Operations." Qeios. doi:*10.32388/ZAPC23.2.
16. ^*Kim Y, et al. (2011). "Development and Control of an Electric Oil Pump for Automatic Transmission-Based Hybrid Electric Vehicle." IEEE Transactions on Vehicular Technology.* ***60****(5):1981–1990. doi:*10.1109/TVT.2011.2140135.
17. ^*Kumar P, Ragavendran S (2023). "Intelligent Helmet for Motorcyclists." International Journal Of Novel Research In Engineering Sciences (IJNRES). 06–04.*

18. ^Moussa S, Ben Ghorbal MJ (2022). *"Shepherd Battery Model Parametrization for Battery Emulation in EV Charging Application." 2022 IEEE International Conference on Electrical Sciences and Technologies in Maghreb (CISTEM). Tunis, Tunisia. 1–6. doi:10.1109/CISTEM55808.2022.10044006.*
19. ^Kumar H, Kumar M, Lindsay M (2016). *"Smart Helmet for Two-Wheeler Drivers." International Journal of Engineering Research And Advanced Technology.* **2***(05):156–159.*
20. ^Oncken J, Chen B (2020). *"Real-Time Model Predictive Powertrain Control for a Connected Plug-In Hybrid Electric Vehicle." IEEE Transactions on Vehicular Technology.* **69***(8):8420–8432. doi:10.1109/TVT.2020.3000471.*
21. ^Ragavendran S, Kumar P (2023). *"Exploring Barriers and Challenges of Electric Vehicles in India and Vehicle-to-Grid Optimization: A Comprehensive Review." International Journal Of Novel Research In Engineering Sciences (IJNRES). 16–19.*
22. ^Lindsay NM, Sunder R S, Karthy N, Krishnan A (2023). *"Smart Cost-Effective Shopping System using Radio Frequency Identification Technology." 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS). Coimbatore, India. 747–750. doi:10.1109/ICAIS56108.2023.10073829.*
23. ^Giordano G, Klass V, Behm M, Lindbergh G, Sjöberg J (2018). *"Model-Based Lithium-Ion Battery Resistance Estimation From Electric Vehicle Operating Data." IEEE Transactions on Vehicular Technology.* **67***(5):3720–3728. doi:10.1109/TVT.2018.2796723.*
24. ^Watta P, Zhang X, Murphey YL (2021). *"Vehicle Position and Context Detection Using V2V Communication." IEEE Transactions on Intelligent Vehicles.* **6***(4):634–648. doi:10.1109/TIV.2020.3044257.*
25. ^Wirasingha SG, Emadi A (2011). *"Classification and Review of Control Strategies for Plug-In Hybrid Electric Vehicles." IEEE Transactions on Vehicular Technology.* **60***(1):111–122. doi:10.1109/TVT.2010.2090178.*
26. ^Liu D, Wang W, Wang L, Jia H, Shi M (2021). *"Dynamic Pricing Strategy of Electric Vehicle Aggregators Based on DDPG Reinforcement Learning Algorithm." IEEE Access.* **9***:21556–21566. doi:10.1109/ACCESS.2021.3055517.*
27. ^Doan V-D, Fujimoto H, Koseki T, Yasuda T, Kishi H, Fujita T (2018). *"Allocation of Wireless Power Transfer System From Viewpoint of Optimal Control Problem for Autonomous Driving Electric Vehicles." IEEE Transactions on Intelligent Transportation Systems.* **19***(10):3255–3270. doi:10.1109/TITS.2017.2774013.*

Declarations

Funding: No specific funding was received for this work.

Potential competing interests: No potential competing interests to declare.

doi.org/10.32388/W0M15I.3