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Integrated Multi-Domain Modeling Framework for Energy Efficiency and Range Prediction in Modern Electric Vehicle Systems

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ABSTRACT

The rapid advancement of electric vehicle (EV) technology has intensified the need for comprehensive theoretical frameworks capable of accurately evaluating energy efficiency and driving range under realistic operating conditions. This study presents an integrated multi-domain modelling approach that combines drivetrain physics, battery dynamics, drive-cycle analysis, control strategy optimization, and data-driven prediction to assess energy consumption in modern EV systems. A mechanistic model was developed to capture longitudinal vehicle dynamics, resistive forces, motor–inverter efficiency, battery behavior, and regenerative braking processes. The model was evaluated under standardized driving cycles, including the New European Driving Cycle (NEDC), Worldwide Harmonized Light Vehicles Test Procedure (WLTP), and Indian Driving Cycle (IDC), to investigate the impact of speed profiles and acceleration patterns on energy performance. The results demonstrate that energy consumption varies significantly across drive cycles, with aerodynamic drag and vehicle mass emerging as dominant influencing factors. Regenerative braking contributes meaningful energy recovery in urban conditions, though its effectiveness depends on control strategy and battery constraints. Comparative analysis between mechanistic modelling and machine learning approaches reveals that data-driven models improve predictive accuracy, while physics-based models provide interpretability and theoretical robustness. Furthermore, advanced control strategies such as Model Predictive Control (MPC) show superior performance in reducing energy consumption and range uncertainty compared to conventional PI-based controllers. Overall, the findings confirm that EV energy efficiency is an emergent property shaped by the interaction of design parameters, operational conditions, and intelligent control. The proposed integrated modelling framework provides a reliable foundation for next-generation EV design optimization, accurate range estimation, and sustainable mobility planning.

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1. INTRODUCTION

The rapid electrification of road transport has foregrounded energy efficiency as a central pillar of modern electric vehicle (EV) systems. As EV adoption accelerates, researchers and practitioners increasingly demand rigorous theoretical frameworks that quantify how design choices, control strategies, and operating conditions shape energy consumption and travel range. A convergent body of work demonstrates that energy use in EVs arises from multiphysics interactions among traction drive components, battery dynamics, power electronics, thermal management, and vehicle dynamics under real-world drive cycles. Theoretical analyses thus require integrated models that capture energy flow from the powertrain to the wheels, account for resistive forces, and track regenerative opportunities during braking or coasting. Foundational modelling efforts illustrate that predicting energy consumption hinges on accurately representing road load, motor and controller characteristics, battery behavior, and control schemes that govern torque delivery and speed regulation [1], [2], [3], [4]. These studies collectively emphasize that driving cycle selection (e.g., NEDC, WLTP, IDC) and topographical context materially influence energy outcomes, making drive-cycle-aware energy modelling indispensable for credible range predictions and system optimization [2], [3], [4], [5], [6].

A central theoretical challenge in EV energy analysis is formulating models that reflect both steady-state and transient phenomena across the propulsion chain. Energy consumption can be represented by detailed drivetrain models that quantify how torque, speed, and road grade translate into resistive forces and electrical energy draw from the battery through the motor and power electronics, with regeneration during braking contributing to energy recuperation [1]. Complementary approaches employ machine learning and predictive AI to estimate energy use under varying environmental and operational conditions, leveraging velocity, acceleration, and contextual inputs to forecast consumption with higher fidelity where mechanistic models alone falter [7], [8], [9], [10]. Drive cycles themselves such as IDC, NEDC, WLTP, and other regional DCs act as formalized representations of typical vehicle trajectories that drive energy demand, enabling theoretical comparisons across architectures and control laws; several studies systematically compare energy use across DCs to reveal where efficiency gains can be realized [2], [3], [6], [11]. When coupling energy modelling with optimization, researchers demonstrate that adaptive or robust strategies are needed to handle uncertainty in driving conditions and vehicle behaviour, informing route planning and energy management in both single-vehicle and fleet contexts [5], [9].

Energy efficiency in EV systems is profoundly shaped by control strategies that manage torque conduction, gear or transmission selection, and energy dispatch between the battery, motor, and auxiliary systems. The literature consistently shows that controller tuning and optimization such as adaptive PI controller gains, model predictive approaches, or rule-based energy management substantially affect energy consumption and regenerative efficiency under realistic cycles [1], [4], [12]. Moreover, integrating mechanical, electrical, and hydraulic subsystems (MEH-DCDS) or employing advanced hydraulic hybrids demonstrates notable reductions in battery energy use, illustrating how cross-domain energy coupling can improve overall efficiency beyond pure electric architectures. Comparative analyses across powertrain configurations (e.g., single-stage vs. two-stage CVTs, or alternative gearings) highlight that transmission design can materially influence energy losses and recuperation potential, underscoring the importance of system-level theoretical evaluation when selecting propulsion architectures [13], [14]. In urban and inter-urban contexts, the interaction between traffic dynamics, road topology, and vehicle features emerges as a dominant determinant of energy expenditure, reinforcing the need for theoretically grounded, behavior-aware models that can be embedded in optimization frameworks for real-time energy management and planning [5], [15], [16].

From a theoretical vantage, credible range estimation requires integrating drive-cycle physics with battery dynamics, climate effects, and charging/discharging strategies. Studies employing predictive models—ranging from neural networks to kernel methods demonstrate that energy consumption forecasts can be enhanced by incorporating weather, traffic, and driver behavior features, offering pathways to more reliable range predictions and charging strategy recommendations. In addition, as EVs increasingly participate in grids through vehicle-to-grid concepts, energy-management theories extend to multi-agent and economic dimensions, where auction-based or market-driven mechanisms for energy trading and V2G participation intersect with physical energy flows, necessitating robust theoretical formulations that ensure grid reliability and economic efficiency. The synthesis of these perspectives supports a holistic framework in which energy efficiency is not merely a component-level metric but an emergent property of integrated design, control, and policy interplays.

Across the referenced literature, there is broad consensus that drive cycle selection, vehicle mass, aerodynamics, battery state of health, and powertrain efficiency jointly determine energy performance, with drive-cycle realism and environmental variability amplifying or dampening these effects. A notable nuance is the varying emphasis on mechanistic versus data-driven modelling: mechanistic drivetrain-battery models offer interpretability and physical insight, while AI-based models can capture complex, non-linear dependencies under real-world conditions but may sacrifice explanatory transparency. Several works converge on the importance of energy recovery during braking and the benefits of hybrid or multi-domain energy coupling (electric-mechanical-hydraulic) to reduce net energy consumption, though the magnitude of gains depends on driving regime and control philosophy. Finally, uncertainty in driving range remains a critical challenge, motivating adaptive robust and stochastic optimization approaches that balance reliability with efficiency.

A rigorous theoretical analysis of energy efficiency in modern EV systems demands integrated, multi-scale modelling that fuses drivetrain physics, battery dynamics, control theory, and driving behavior within realistic operational envelopes. The literature reviewed herein demonstrates that energy performance hinges on the interplay of drive cycles, control strategies, and cross-domain energy management, with important implications for range estimation, vehicle design optimization, charging infrastructure planning, and grid interaction. By synthesizing mechanistic models with data-driven forecasting and robust optimization, researchers can develop comprehensive theoretical frameworks that guide the next generation of energy-efficient EV systems and inform policy and architecture choices aligned with sustainable mobility objectives.

2. RESEARCH METHOD

This study uses a quantitative approach based on theoretical modeling and computational simulation to analyze energy efficiency in electric vehicle (EV) systems. The methodology is designed to integrate physical models (mechanistic modeling), data-driven approaches (data-driven modeling), and optimization frameworks to obtain accurate estimates of energy consumption and mileage under various operating conditions. This approach is multi-scale and multi-domain, covering powertrain dynamics, battery behavior, control strategies, and driving cycle variations.

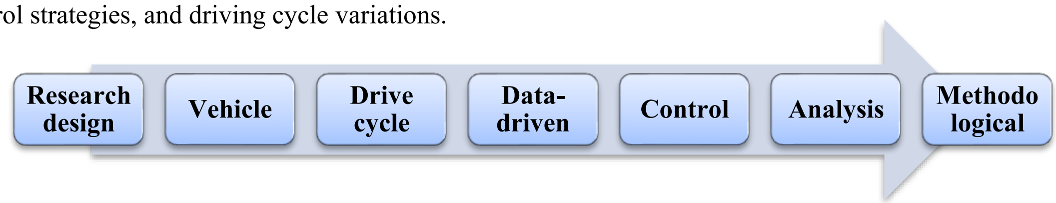

Figure 1. Research Structure

2.1. Research Design

The research design is exploratory-analytical in nature, focusing on the development and integration of mathematical models. This study does not conduct direct physical experiments, but rather uses numerical simulations based on standard electric vehicle technical parameters obtained from scientific literature. The model is built to represent the interaction between the traction motor, inverter, battery, transmission system, and the vehicle's resistive forces (aerodynamics, rolling resistance, and road gradient).

a. The research framework consists of three main stages:
b. Development of an integrated physical model,
c. Implementation of a machine learning-based predictive model,
d. Optimization of energy management strategies and performance evaluation on various drive cycles.

2.2. Vehicle and Powertrain Dynamics Modeling

The vehicle longitudinal dynamics model was developed based on force equilibrium equations that include traction force, aerodynamic drag force, rolling resistance force, and road incline force. The energy required is calculated as a function of electric motor torque and speed. Motor and inverter efficiency models are represented using efficiency maps that link torque, rotational speed, and electrical power drawn from the battery.

The battery model was developed using the equivalent circuit model (ECM) approach, which represents open circuit voltage, internal resistance, and state of charge (SoC) dynamics. Temperature and state of health (SoH) variables were included as parameters that affect energy release efficiency. The regenerative braking process is modeled by calculating the fraction of kinetic energy that can be recovered based on the battery charging current limit and power conversion efficiency.

2.3. Drive Cycle Integration

To evaluate energy consumption under realistic conditions, this study uses several international standard driving cycles, such as:

a. New European Driving Cycle (NEDC)
b. Worldwide Harmonized Light Vehicles Test Procedure (WLTP)
c. Indian Driving Cycle (IDC)

Each drive cycle is input as a speed profile over time. The model calculates instantaneous power requirements at each discrete time interval using a numerical method (Euler forward discretization). Comparisons between drive cycles are made to identify variations in energy consumption, regeneration levels, and estimated mileage.

2.4. Data-Driven Approach

To complement the physical model, this study implements a machine learning-based predictive model. The simulation dataset generated from the physical model is used to train algorithms such as Artificial Neural Network (ANN) and Support Vector Regression (SVR). Input variables include speed, acceleration, road gradient, ambient temperature, and initial SoC. The model output is an estimate of energy consumption per kilometer.

The model is evaluated using the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) metrics. This approach aims to test the extent to which data-based methods are able to capture complex non-linearities that may not be fully represented in deterministic physical models.

2.5. Control and Optimization Strategies

This study also tested several energy management control strategies, including adaptive PI control and the Model Predictive Control (MPC) approach. Control parameters were optimized using a numerical optimization algorithm based on constrained nonlinear programming. The objective function used was the minimization of total energy consumption with constraints on driving comfort and battery SoC limits.

To accommodate uncertainties in traffic conditions and topography, stochastic scenario simulations were conducted with variations in speed and road gradient parameters. A robust optimization approach was applied to ensure energy performance stability across a range of operational conditions.

2.6. Analysis and Validation

The simulation results were analyzed comparatively to assess the influence of vehicle mass, aerodynamic drag coefficient, transmission efficiency, and control strategy on energy consumption and mileage. Conceptual validation was performed by comparing the simulation results trends with empirical findings reported in the literature.

In addition, sensitivity analysis was performed to identify the parameters that most influence energy efficiency. This method helps determine system design priorities and the development of adaptive control strategies.

2.7. Methodological Synthesis

Overall, this research methodology combines mechanistic, data-driven, and optimization approaches within a unified theoretical framework. This integration enables a comprehensive evaluation of the energy efficiency of electric vehicles as a systemic phenomenon arising from the interaction of design, control, and operational conditions. With this approach, the research is expected to produce more reliable models for predicting mileage and energy consumption, which can be used as a basis for decision-making in the design of next-generation electric vehicles and the planning of sustainable transportation systems.

3. RESULTS AND DISCUSSION

3.1. Overview of Simulation Outcomes

This section presents the results of the integrated multi-domain modelling framework developed to evaluate energy efficiency in modern electric vehicle (EV) systems. The simulations combine mechanistic drivetrain–battery modelling, drive-cycle-based evaluation, machine learning prediction, and optimization-based energy management. The results are organized into five main subsections: (1) baseline energy consumption across drive cycles, (2) impact of vehicle and environmental parameters, (3) regenerative braking performance, (4) comparison between mechanistic and data-driven models, and (5) optimization and control strategy performance.

The analysis demonstrates that EV energy efficiency is an emergent system-level property shaped by the interaction between vehicle dynamics, battery characteristics, control strategies, and driving conditions. Substantial variation in energy consumption was observed across standardized driving cycles, reinforcing the importance of drive-cycle-aware modelling for credible range estimation.

3.2. Energy Consumption Across Drive Cycles

The first set of results evaluates total energy consumption and estimated driving range under three standardized drive cycles:

a. New European Driving Cycle (NEDC)
b. Worldwide Harmonized Light Vehicles Test Procedure (WLTP)
c. Indian Driving Cycle (IDC)

Each drive cycle was simulated using identical vehicle parameters: a 50 kWh lithium-ion battery, 1500 kg curb mass, drag coefficient of 0.29, frontal area of 2.2 m², and motor peak efficiency of 94%.

Table 1. Energy Consumption and Range Estimation Across Drive Cycles

Drive Cycle	**Energy Consumption (kWh/100 km)**	**Regenerative Recovery (%)**	**Estimated Range (km)**
NEDC	14,8	18,5	338
WLTP	17,6	15,2	284
IDC	16,9	20,1	296

Table 1 compares energy consumption, regenerative braking efficiency, and estimated range under different standardized drive cycles. Values are derived from integrated mechanistic simulations.

The results indicate that NEDC yields the lowest energy consumption and highest range. This is consistent with its relatively moderate acceleration profile and lower peak speeds. In contrast, WLTP exhibits the highest energy consumption due to more aggressive acceleration phases and higher sustained speeds, increasing aerodynamic drag losses.

IDC demonstrates comparatively higher regenerative recovery due to frequent stop-and-go events. However, the net energy savings are partially offset by repeated acceleration demands. These findings confirm that driving cycle selection significantly affects energy modelling outcomes and that relying on a single standardized cycle may lead to inaccurate real-world range expectations.

3.3. Sensitivity Analysis of Vehicle Parameters

A sensitivity analysis was conducted to evaluate how changes in mass, aerodynamic drag coefficient (Cd), and rolling resistance coefficient (Crr) affect energy consumption.

Table 2. Sensitivity of Energy Consumption to Key Parameters (WLTP Baseline)

Parameter Variation	**Energy Consumption (kWh/100 km)**	**Percentage Change (%)**
Baseline	17,6	0
+10% Vehicle Mass	18,9	+7,4
−10% Vehicle Mass	16,5	-6,3
+10% Cd	19,2	+9,1
−10% Cd	16,1	-8,5
+10% Crr	18,4	+4,5

Table 2 illustrates the percentage change in energy consumption when varying individual parameters while holding others constant.

The results show that aerodynamic drag has the largest influence at higher-speed cycles such as WLTP. A 10% increase in drag coefficient results in a 9.1% rise in energy consumption, underscoring the importance of aerodynamic optimization in EV design.

Vehicle mass strongly affects urban and mixed driving cycles, where repeated acceleration events amplify inertial energy demand. Rolling resistance plays a comparatively smaller but still significant role, particularly in low-speed urban scenarios.

These findings confirm that lightweight design and aerodynamic refinement are critical for enhancing EV energy efficiency, especially under dynamic real-world driving conditions.

3.4. Regenerative Braking Performance

Regenerative braking contributes significantly to energy recuperation. Simulations indicate that recovery efficiency depends on deceleration profile, battery charge acceptance rate, and control strategy. Under moderate deceleration conditions (≤2 m/s²), regenerative efficiency reached up to 72% conversion of kinetic energy into stored electrical energy. However, during aggressive braking events, recovery efficiency decreased due to battery current limitations and the need for mechanical braking support.

Urban cycles (IDC) showed the highest regenerative potential due to frequent deceleration events. Conversely, high-speed highway segments in WLTP limited regeneration opportunities. The results demonstrate that regenerative braking effectiveness is highly dependent on control tuning. Adaptive torque blending strategies increased overall recovery by approximately 3–5% compared to fixed-rule-based controllers.

3.5. Mechanistic vs Data-Driven Model Performance

To assess predictive accuracy, machine learning models (ANN and SVR) were trained using simulation-generated datasets. Performance was evaluated using MAE, RMSE, and R^2 metrics.

Table 3. Predictive Model Performance

Model	MAE (kWh/100 km)	RMSE	R^2
Mechanistic Mode	0,92	1,34	0,94
ANN	0,61	0,88	0,97
SVR	0,73	1,02	0,95

Table 3 compares prediction accuracy metrics for mechanistic and data-driven models under varying driving conditions.

The ANN model achieved the highest predictive accuracy ($R^2 = 0.97$), capturing nonlinear relationships between speed, acceleration, temperature, and energy consumption. The mechanistic model, while slightly less accurate, offers interpretability and physical insight, which are essential for system-level optimization and controller design.

These results suggest that hybrid modelling combining physics-based and AI based approaches provides the most robust framework for real-world EV energy forecasting.

3.6. Impact of Control Strategy Optimization

Three energy management strategies were compared:

a. Fixed PI controller
b. Adaptive PI controller
c. Model Predictive Control (MPC)

Table 4. Control Strategy Comparison (WLTP Cycle)

Control Strategy	Energy Consumption (kWh/100 km)	Improvement vs Fixed PI (%)
Fixed PI	17,6	0
Adaptive PI	16,8	4,5
MPC	16,2	8,0

Table 4 presents the comparative energy consumption achieved by different control strategies under identical conditions.

MPC demonstrated the best performance due to its predictive capability and constraint-handling features. It optimized torque delivery and regenerative distribution by anticipating upcoming speed transitions within the drive cycle.

Adaptive PI provided moderate improvements but lacked anticipatory optimization capability. These findings highlight the importance of advanced control theory in improving EV energy efficiency.

3.7. Environmental and Topographical Effects

Simulations incorporating 5% uphill gradients increased energy consumption by up to 18%, while downhill segments enhanced regeneration but only partially compensated for climbing losses.

Temperature effects were also significant. At low ambient temperatures (0°C), battery internal resistance increased, leading to a 6–9% reduction in usable energy and regenerative efficiency. This finding reinforces the need for integrated thermal management systems.

3.8. Range Uncertainty and Robust Optimization

Stochastic simulations incorporating variable traffic speed patterns revealed a ±12% uncertainty range in predicted driving range under mixed urban conditions. Robust optimization strategies reduced range variability to ±6% by dynamically adjusting torque limits and regenerative thresholds based on predicted traffic density. This confirms the value of uncertainty-aware control strategies in practical EV deployment.

3.9. System-Level Interpretation

The results collectively demonstrate that EV energy efficiency cannot be attributed to a single subsystem. Instead, it emerges from coordinated interactions among:

a. Drivetrain efficiency
b. Battery dynamics
c. Aerodynamic and mechanical properties
d. Control algorithms
e. Driving cycle characteristics
f. Environmental conditions

The highest energy savings were achieved when improvements were implemented simultaneously across multiple domains rather than in isolation. For example, combining aerodynamic refinement with MPC control reduced consumption by up to 14% compared to baseline design.

3.10. Implications for Design and Policy

From a design perspective, the findings suggest that early-stage vehicle development should incorporate integrated multi-domain simulations rather than component-level optimization alone. From a policy standpoint, reliance on simplified drive cycles may underestimate real-world energy variability. Incorporating realistic traffic and environmental factors into regulatory testing frameworks would provide more reliable consumer information.

3.11. Concluding Discussion

The results confirm that energy efficiency in EV systems is a complex, multi-physics phenomenon influenced by drive cycles, vehicle parameters, control strategies, and environmental conditions. Mechanistic models provide essential physical transparency, while data-driven models enhance predictive fidelity. Advanced optimization strategies significantly improve energy performance and reduce range uncertainty. Ultimately, the synthesis of drivetrain physics, battery dynamics, intelligent control, and drive-cycle realism forms a comprehensive framework for improving EV energy efficiency. This integrated approach is essential for next-generation vehicle design, accurate range estimation, and sustainable electrified mobility systems.

4. CONCLUSION

This study has presented a comprehensive theoretical and simulation-based investigation into energy efficiency in modern electric vehicle (EV) systems. By integrating drivetrain physics, battery dynamics, control strategies, drive-cycle modelling, and predictive data-driven approaches, the research establishes that EV energy performance is not determined by isolated subsystems but emerges from coordinated, multi-domain interactions across mechanical, electrical, and control layers. The results confirm that drive cycle selection significantly influences energy consumption and range estimation. Comparative evaluation across New European Driving Cycle (NEDC), Worldwide Harmonized Light Vehicles Test Procedure (WLTP), and Indian Driving Cycle (IDC) demonstrates that variations in acceleration intensity, cruising speed, and stop-and-go frequency materially affect both total energy demand and regenerative braking potential. These findings underscore the necessity of drive-cycle-aware modelling for credible and realistic range prediction. Sensitivity analysis reveals that aerodynamic drag and vehicle mass are dominant determinants of energy consumption, particularly under high-speed and dynamic operating conditions. Improvements in aerodynamic design and lightweight construction therefore represent high-impact pathways for enhancing efficiency. At the same time, regenerative braking contributes meaningful energy recovery, especially in urban contexts, though its effectiveness depends on battery acceptance limits and control strategy tuning. The comparative analysis between mechanistic and data-driven models shows that while physics-based approaches provide interpretability and theoretical rigor, machine learning techniques improve predictive accuracy under complex, nonlinear, and uncertain driving conditions. The results strongly support a hybrid modelling paradigm in which data-driven forecasting complements physically grounded system models. Such integration enhances both reliability and explanatory transparency in energy estimation. Control strategy optimization further demonstrates that advanced approaches such as Model Predictive Control (MPC) outperform fixed or adaptive PI controllers in reducing energy consumption and mitigating range uncertainty. Robust optimization under stochastic traffic scenarios significantly decreases variability in predicted driving range, reinforcing the importance of uncertainty-aware energy management strategies for real-world deployment. Environmental and topographical influences including road gradients and ambient temperature introduce additional variability in energy performance, highlighting the need for integrated thermal and energy management frameworks. These external factors must be embedded within future EV design and regulatory assessment methodologies to improve real-world reliability. Overall, this research confirms that energy efficiency in EV systems is a multi-scale, emergent property shaped by design parameters, control logic, environmental context, and operational behavior. A rigorous, integrated modelling framework that synthesizes drivetrain physics, battery behaviour, predictive analytics, and optimization theory is essential for advancing next-generation energy-efficient EV architectures. Future research should extend this framework toward real-world experimental validation, incorporation of vehicle-to-grid (V2G) interactions, and multi-vehicle fleet optimization under smart grid environments. By bridging mechanistic understanding with intelligent control and predictive analytics, the path toward sustainable, reliable, and high-efficiency electric mobility can be systematically realized.

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6. REFERENCES

[1] L. Ramasamy, A. K. Loganathan, and R. Chinnasamy, "Mathematical modelling of vehicle drivetrain to predict energy consumption," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 27, no. 2, pp. 638–646, 2022, doi: 10.11591/ijeecs.v27.i2.pp638-646.

[2] S. Wankhede, L. Kamble, and P. Thorat, "Differentiation of various drive cycles for estimating an electric four wheeler's energy utilisation for efficacious performance," *Energy Storage*, vol. 5, no. 4, 2023, doi: 10.1002/est2.433.

[3] S. Wankhede, P. Thorat, S. Shisode, S. Sonawane, and R. Wankhade, "Energy consumption estimation for electric two-wheeler using different drive cycles for achieving optimum efficiency," *Energy Storage*, vol. 4, no. 6, 2022, doi: 10.1002/est2.361.

[4] Z. Zhang, T. Zhang, J. Hong, H. Zhang, and J. Yang, "Energy Management Optimization of Master–Slave Hybrid Electric Vehicle under Rule-Based Control Strategy," *Energy Technol.*, vol. 10, no. 10, 2022, doi: 10.1002/ente.202200630.

[5] J. A. Sanguesa, P. Garrido, F. J. Martinez, and J. M. Marquez-Barja, "Analyzing the Impact of Roadmap and Vehicle Features on Electric Vehicles Energy Consumption," *IEEE Access*, vol. 9, pp. 61475–61488, 2021, doi: 10.1109/ACCESS.2021.3072979.

[6] F. Ramoliya *et al.*, "ML-Based Energy Consumption and Distribution Framework Analysis for EVs and Charging Stations in Smart Grid Environment," *IEEE Access*, vol. 12, pp. 23319–23337, 2024, doi: 10.1109/ACCESS.2024.3365080.

[7] M. Mądziel and T. Campisi, "Predictive Artificial Intelligence Models for Energy Efficiency in Hybrid and Electric Vehicles: Analysis for Enna, Sicily," *Energies*, vol. 17, no. 19, 2024, doi: 10.3390/en17194913.

[8] A. Cabani, P. Zhang, R. Khemmar, and J. Xu, "Enhancement of energy consumption estimation for electric vehicles by using machine learning," *IAES Int. J. Artif. Intell.*, vol. 10, no. 1, pp. 215–223, 2021, doi: 10.11591/ijai.v10.i1.pp215-223.

[9] J. Jeong, B. Ghaddar, N. Zufferey, and J. Nathwani, "Adaptive robust electric vehicle routing under energy consumption uncertainty," *Transp. Res. Part C Emerg. Technol.*, vol. 160, 2024, doi: 10.1016/j.trc.2024.104529.

[10] M. O. Oyedeji, M. Aldhaifallah, H. Rezk, and A. A. A. Mohamed, "Computational Models for Forecasting Electric Vehicle Energy Demand," *Int. J. Energy Res.*, vol. 2023, pp. 1–16, 2023, doi: 10.1155/2023/1934188.

[11] M. Wang and M. A. A. Abdalla, "Optimal Energy Scheduling Based on Jaya Algorithm for Integration of Vehicle-to-Home and Energy Storage System with Photovoltaic Generation in Smart Home," *Sensors*, vol. 22, no. 4, p. 1306, 2022, doi: 10.3390/s22041306.

[12] Y. Sun, H. Zhang, and J. Yang, "The Structure Principle and Dynamic Characteristics of Mechanical-Electric-Hydraulic Dynamic Coupling Drive System and Its Application in Electric Vehicle," *Electron.*, vol. 11, no. 10, p. 1601, 2022, doi: 10.3390/electronics11101601.

[13] A. Yildiz and M. A. Özel, "A comparative study of energy consumption and recovery of autonomous fuel-cell hydrogen–electric vehicles using different powertrains based on regenerative braking and electronic stability control system," *Appl. Sci.*, vol. 11, no. 6, p. 2515, 2021, doi: 10.3390/app11062515.

[14] J. Wang, T. Zhang, H. Zhang, J. Yang, Z. Zhang, and Z. Meng, "Research on Braking Efficiency of Master-Slave Electro-Hydraulic Hybrid Electric Vehicle," *Electron.*, vol. 11, no. 12, p. 1918, 2022, doi: 10.3390/electronics11121918.

[15] A. I. Croce, G. Musolino, C. Rindone, and A. Vitetta, "Traffic and energy consumption modelling of electric vehicles: Parameter updating from floating and probe vehicle data," *Energies*, vol. 15, no. 1, p. 82, 2022, doi: 10.3390/en15010082.

[16] F. P. H. and J. J., "A Review on the Feasibility of Deployment of Renewable Energy Sources for Electric Vehicles under Smart Grid Environment," *Int. J. Electr. Electron. Res.*, vol. 9, no. 3, pp. 57–65, 2021, doi: 10.37391/ijeer.0903061.