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ESTIMATION OF ENERGY CONSUMPTION IN REAL-TIME EV SENSOR DATA THROUGH EXPLAINABLE AI AND MACHINE LEARNING ALGORITHM

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Abstract— Electric Vehicles (EVs) represent a transformative shift in transportation, promising reduced dependence on fossil fuels and lower emissions. EVs rely on sensors to gather vast amounts of real-time data on parameters such as speed, acceleration, battery charge, and environmental factors, which all play a crucial role in determining energy efficiency. This research focuses on real-time estimation of energy consumption using machine learning and explainable AI (XAI) to interpret sensor data effectively. While previous studies primarily focused on evaluating energy usage through traditional methods or basic machine learning algorithms, this work leverages advanced models like Random Forest and Neural Networks, trained on extensive real-time data from Battery Electric Vehicles (BEVs) across varied driving conditions. Additionally, the SHapley Additive exPlanations (SHAP) method is utilized to enhance model interpretability, offering insights into how different parameters—such as vehicle speed and battery current—affect energy consumption. This explainability not only enables more accurate predictions of energy use but also assists in identifying key factors influencing energy inefficiency in real-time scenarios. The proposed approach enhances prior work by improving prediction accuracy and adaptability through XAI, supporting more precise energy management strategies. Ultimately, this research contributes to optimizing EV performance, extending battery life, and reducing range anxiety, which are critical for accelerating EV adoption and guiding future policies on transportation electrification.

Keywords— *SHAP, Electric Vehicles, practical driving, random forest, energy efficiency.*

INTRODUCTION

As Battery Electric Vehicles (BEVs) gain popularity, optimizing their energy consumption remains a significant challenge. The efficiency of a BEV is influenced by various factors such as driving habits, terrain, climate conditions, and vehicle load, which impact battery usage and range. Despite advances in BEV technology, accurately predicting energy consumption in real-world driving conditions is still a complex task. The traditional methods used for estimating BEV energy consumption often rely on simplified models that only consider average conditions, such as speed, distance, and a few environmental factors [1]. These models are inadequate for the variability encountered in actual driving situations.

Moreover, as BEVs operate in dynamic environments, the failure to account for real-time changes in driving conditions can lead to inaccurate energy predictions, causing issues such as range anxiety and inefficient battery usage. Drivers may find themselves running out of battery earlier than expected, or unable to optimize their vehicle's energy performance. For BEV manufacturers, poor energy estimation results in inefficient battery designs and limited improvements in energy management systems [2].

The challenge, therefore, is to develop a robust and adaptive energy consumption model that can incorporate real-time driving conditions and vehicle behaviour to make more accurate predictions. The solution lies in utilizing the data generated by advanced vehicle sensors and employing machine learning algorithms to process this data, detect patterns, and make precise energy consumption forecasts.

CURRENT SCENARIO

Battery Electric Vehicle (BEV) energy consumption is typically estimated through rule-based methods or physics-based models [3], which take into account variables like speed, road gradient, and the vehicle's mass. While these models are computationally simple, they fall short in representing real-world scenarios where energy consumption is influenced by numerous factors, including sudden changes in driving behavior (e.g., rapid acceleration or deceleration), traffic conditions, and environmental variations such as wind resistance and temperature fluctuations [4].

The development stage of electric vehicles (EVs) is marked by rapid growth and increasing adoption worldwide. In 2023, nearly one in five cars sold globally was electric, with sales reaching almost 14 million units. This surge is driven by advancements in battery technology, improved range, and a growing commitment to reducing carbon emissions. Major markets like China, Europe, and the United States are leading the charge, with electric cars accounting for a significant share of new car registrations.

Despite this progress, several challenges remain, including the need for more extensive charging infrastructure, higher upfront costs compared to internal combustion engine vehicles, and range anxiety among consumers. To address these issues, governments and industry stakeholders are implementing various techniques and strategies. For instance, expanding the network of fast-charging stations can help alleviate range anxiety, while advancements in battery technology are reducing costs and improving vehicle range [5]. Moreover, policy support and incentives such as tax breaks, subsidies, and grants are making EVs more affordable and attractive to consumers.

The future looks promising, with projections indicating that EVs could make up more than 50% of global car sales by 2035. Continuous innovation, investment in infrastructure, and supportive policies will play crucial roles in overcoming current obstacles and accelerating the transition to a low-carbon economy. The findings indicate that the BEVs in this research used an average of 148.03 Wh/km in energy consumption. To delve deeper into the factors influencing this energy usage, a thorough approach is made using SHapley Additive exPlanations (SHAP) method. This analysis illuminated the relationship between vehicle speed, battery current, and energy usage, with a particular focus on urban driving. These insights help enhancing the energy of BEVs, also inform transportation electrification rules, ultimately supporting the broader adoption of electric vehicles.[6]. In this study, we explore the use of machine learning to provide a more precise and comprehensive approach to predicting BEV energy consumption. The findings of this research will not only benefit BEV manufacturers by enabling better energy management systems but also contribute to the broader goal of making electric vehicles more practical and appealing to consumers.

LITERATURE SURVEY

Zhou reviewed machine learning applications in EV energy prediction, focusing on how real-time machine learning algorithms can optimize battery and powertrain management. Their study emphasizes the use of deep reinforcement learning in vehicle routing and energy allocation, showing substantial improvements in efficiency for urban transportation. Ayetor investigated the application of model predictive control (MPC) in multi-phase electric drives. This approach has been proven effective in managing complex control variables in EV powertrains, providing high fault tolerance and minimizing harmonic distortion. Their findings highlight MPC's potential for enhancing dynamic response and robustness in EVs under varied operational conditions.

Gersdorf, T [6] reviewed battery thermal management systems, exploring advanced cooling methods like phase-change materials and liquid cooling. Their work provides insights into how these systems extend battery lifespan and maintain optimal temperature ranges, which is crucial for EV safety and performance

Lundberg, S. M., [7] addressed the lifecycle of EV batteries, focusing on second-life applications and recycling. They examined circular economy principles, showing that repurposing EV batteries for energy storage in renewable applications significantly enhances sustainability.

Donkers, A [9] reviewed advancements in fast-charging technology, specifically focusing on battery chemistry and charging protocols. They found that lithium iron phosphate and solid-state battery chemistries offer promising pathways for reducing charging time without compromising safety.

Suttakul, P [11] proposed a state-of-the-art energy management strategy (EMS) for hybrid electric vehicles (HEVs), using real-time optimization to balance power demand and fuel efficiency. Their EMS model adapts based on real-world driving data, improving energy distribution across battery and fuel sources.

Achariyaviriya, W [15] analyzed autonomous EVs and their interaction with smart grids, emphasizing the benefits of bi-directional charging. Their research demonstrated how vehicle-to-grid (V2G) integration helps balance grid loads and supports renewable energy uptake. Degen studied the impact of multiphase motors on EV powertrains, outlining advantages in fault tolerance and power density. Their findings indicate that five- and six-phase machines, paired with advanced modulation techniques, could become mainstream in future EV designs.

Wei, H [12] examined the design of in-wheel motors for lightweight EVs, highlighting how this technology improves torque and braking capabilities. Their model suggests that reducing transmission elements lowers vehicle weight and enhances energy efficiency.

Pignatta, G [16] explored battery regeneration and found that improved battery regeneration methods could enhance performance in aging EVs, thereby reducing the demand for new materials and supporting sustainability. Tan developed an advanced predictive model for EV range estimation, incorporating variables like driver behavior and external conditions. Their study shows that such predictive models can help mitigate range anxiety by offering more accurate range estimates. Zhang [14] analyzed the role of permanent magnet and magnet-less machines in EVs, focusing on efficiency and cost-effectiveness. They concluded that advances in material science and electromagnetic design are central to producing more efficient and affordable EV motors.

METHODOLOGY

The research approach is akin to conventional machine learning methods. The first step is data collecting, wherein various sources are consulted to obtain information on how long electric car batteries last. Next, the data is refined and standardised for dependability through an extensive data pre-processing step. The model is directed by feature selection, which finds important factors that affect battery life. For training and testing, the dataset is then split into two sets. The training set serves to familiarise the model with patterns in the data, while the testing set evaluates its performance using fresh data. An optimised model for extending battery life is built using machine learning methods. Ultimately, the accuracy and efficiency of the model are assessed by the use of relevant measures.[17][18]

The present work employed a rigorously developed and established experimental approach to ascertain and hence guaranteeing dependable & precise outcomes. The approach, considering specs, path options, information collecting tools, and energy usage computations, are covered in length in this part. In order to collect continuous data from cars, GPS and Onboard Diagnostics (OBD) are set up in cars and these can be easily accessed using applications. [19][20]

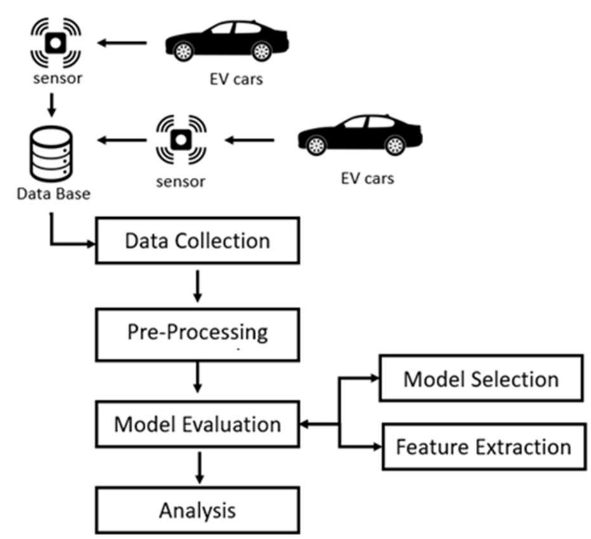


Fig. 1. System Architecture

In the context of predicting Battery Electric Vehicle (BEV) energy consumption, data collection is a critical step as it serves as the foundation for model development. The data used in this study is gathered from multiple sensors installed in BEVs, capable of monitoring real-time vehicle and environmental parameters. These sensors track various variables, including speed, acceleration, braking force, battery state of charge (SoC), motor temperature, road gradient, and external conditions such as temperature and wind speed.

Data Collection

In Thailand, datasets collected for electric vehicles (EVs) include information on battery status, charging patterns, energy consumption, and vehicle performance, gathered through various sensors and systems installed in EVs. An extensive driving dataset with over thirty-five thousand information was obtained by utilising a variety of in-car sensors that were linked with the OBD. The vehicle's location was precisely tracked using GPS technology during the data gathering procedure. This dataset included several BEVs, and the factors influencing their energy usage were carefully taken into account. The dependable capture of observable variables was ensured by the steady frequency of 1 Hz used for data collecting.[21][22]

TABLE I. DATASET STATISTICS

Features	**Unit**	**Range**	**Mean**	**SD**
Speed *(v)*	Km/h	1.00, 138.61	53.2915	32.2183
Acceleration *(a)*	m/s^2	-5.79, 15.99	0.0508	0.6404
Road slope *(m)*	%	-69.85, 69.98	0.0611	10.8670
Battery current *(I)*	A	-246.20, 335.10	11.0517	43.0538
State of charge *(SOC)*	%	13.20, 97.97	50.4685	22.2618

Preprocessing

Data pre-processing involves many sub-steps as explained below:

Data Cleaning
This involves handling missing values, outliers, and sensor errors. Missing data points are imputed using statistical methods (e.g., mean or median imputation) or advanced techniques like interpolation for time-series data. Outliers are detected and removed or treated using methods like z-scores or IQR (Interquartile Range) analysis to prevent skewing the model.

Data Normalization
Since the sensor data includes variables with different scales (e.g., speed in km/h, temperature in °C), normalization or standardization is applied. This helps ensure that all features contribute equally to the model's learning process. Min-max scaling or z-score normalization is used to bring the values within a consistent range, typically between 0 and 1.

Data Aggregation
For time-series data, aggregation techniques are applied to reduce data granularity and focus on key patterns. This may involve averaging sensor readings over specific time windows, calculating rolling statistics (e.g., moving averages), or summarizing driving sessions.

Data Transformation
Certain features, like road gradient or battery SoC, may need to be transformed to highlight their impact on energy consumption. This could involve generating additional features like derivative features (e.g., rate of change of acceleration) or converting categorical variables (e.g., driving

modes) into one-hot encoded vectors.

Finally, standardisation was done before analysis to lessen the effect of different ranges within the input characteristics. Moreover, the Yeo–Johnson non-linear transformation method was used to improve the dataset's normal distribution properties [23]. The training process is much more stable and efficient as a result of these preprocessing processes. Factors are reduced by standardising characteristics, obtaining a guaranteeing resilience and promoting effective model training.

Model Evaluation And Execution

Next, the test-train splitting technique is applied to divide the Pre-Processed dataset. The test data and the train data are two distinct sets that comprise the total dataset. Test data makes up 20% of the dataset and is used to evaluate the model's functionality, accuracy, and other metrics. Eighty percent of the dataset consists of the Train data. The model is trained using the recommended algorithmic strategies on this train set of data. A pattern found in the train data is used by the algorithm to learn. In order to evaluate the model's effectiveness over a range of scenarios, this data must be partitioned.[24]

The most important part of the model selection process is figuring out which machine learning algorithm is most appropriate for a certain task. In order to make an informed choice, a number of models must be tested and their performance on a test set assessed.[25].

Utilising the 10-fold cross-validation technique that divides data as 10 subsets, 9 of which are used development. The effectiveness of these methods on the characteristics of the input and aim output dataset was evaluated, as seen in Figure 1. As a result, 10 loops are used in the training process, and the precision of the process was calculated by averaging the results from each loop [26][27]. Ten-fold cross-validation is a technique that may be used to obtain an accurate assessment of an ML model's capacity for generalisation as well as to choose the best collection of hyperparameters regarding a particular dataset.

An important part of the model building process is evaluating the correctness of the machine learning technique. The models were assessed with assessment measures, such as the RMSE, MAPE, R^2. These assessment measures were used to give an unbiased value in investigation.[28] The following formulas can be used to compute these metrics:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(EC_i^P - EC_i^R\right)^2}{\sum_{i=1}^{n}\left(EC_i^R - \text{mean}\left(EC_i^R\right)\right)^2} \qquad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(EC_i^P - EC_i^R)^2}{n}} \qquad (2)$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{EC_i^P - EC_i^R}{EC_i^R}\right| \qquad (3)$$

Where,

R2 – Coefficient of Determination,

RMSE – Root Mean Squared Value,

MAPE – Mean Absolute Percentage Error,

EC_i^P – is the predicted electric consumption (or energy consumption) at instance i,

EC_i^R – is the real (actual) electric consumption at instance i,

n – is the number of observations.

The anticipated energy consumption is represented by $\mathbf{D}C_i^{\mathrm{P}}$ in this case, the number of samples is represented by n, and the accompanying real-world energy consumption is shown by $\mathbf{D}C_i^{\mathrm{R}}$. Higher R^2 and lower RMSE and MAPE values, on the other hand, typically denote better model performance since they show less of a difference between the expected and actual results. Larger R^2 value shows better correlation. Similarly lower values of MAPE and RMSE shows less error, these assessment metrics function as trustworthy markers of the model's correctness.[29][30].

Predicted Electric Consumption represents the estimated or predicted amount of electric energy consumed by the EV at a specific time instance, i. Predictions are typically generated by a model based on historical data, current conditions, and vehicle operational parameters. Real (Actual) Electric Consumption is the actual amount of electric energy consumed by the EV at the same time instance, i, measured directly from the vehicle or battery monitoring systems. Number of Observations (n) denotes the total number of time instances (data points) over which the electric consumption measurements—both predicted and actual—are recorded. It provides the dataset size used for analyzing the accuracy of the energy consumption model.

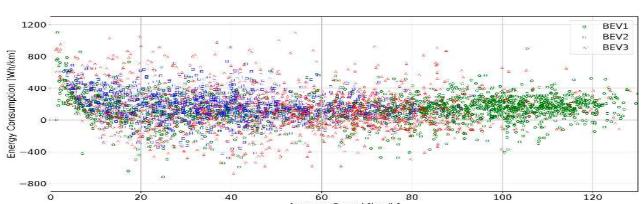
These terms are commonly used in studies aiming to minimize the error between predicted and actual energy consumption, enhancing EV range prediction accuracy. Metrics like Mean Absolute Error (MAE) or Mean Squared Error (MSE) are calculated using these predictions and actual values to assess and improve the prediction model’s performance.

Real World Energy Consumption

Based on RDE, paths may be divided into urban and rural categories, offering a range of driving circumstances. Several short-distance excursions were used for checking power usage of vehicles to precisely calculate under specific conditions. Compared to taking the average of a full journey, this method enables a more precise capture of changes in energy use. Power usage for BEVs in relation to mean speed is shown in Figure 3.

Fig. 2. Mean power consumption of BEVs

It's data for many short-distance excursions at different average speed ranges. The particular speed ranges connected to the data might be taken into consideration while classifying the different route modes. Furthermore, taking into account BEV energy consumption, the average carbon emissions for the urban and rural modes were found to be 95.72 and 79.19 gCO2eq/km, respectively. Vital



to remember that Figure 4 shows the actual driving [31]

Model Selection and Interpretation

Various assessment metrics were used in this work to assess how well the suggested techniques performed in forecasting power usage of BEVs. SHAP values were applied in this study for both local and global interpretations, enhancing our understanding of how each feature influences BEV energy consumption. Local interpretations are crucial for analysing specific driving scenarios, where factors such as high acceleration or road gradient may significantly increase energy usage in individual predictions. For instance, a force plot allows us to visualize how specific features contributed to a particular prediction, showing whether a higher energy prediction was driven by high speed or a low state of charge.

Global interpretations, represented by bees warm and summary plots, reveal the overall importance of features across all predictions. These plots indicate that battery current, vehicle speed, and road gradient consistently rank as the most influential factors affecting energy consumption, guiding broader strategies for optimizing BEV performance. The summary plot, in particular, demonstrates how varying levels of each feature impact predictions, offering insights for both real-time energy management and long-term efficiency improvements.

TABLE II. RUN-TIME AND METRICS

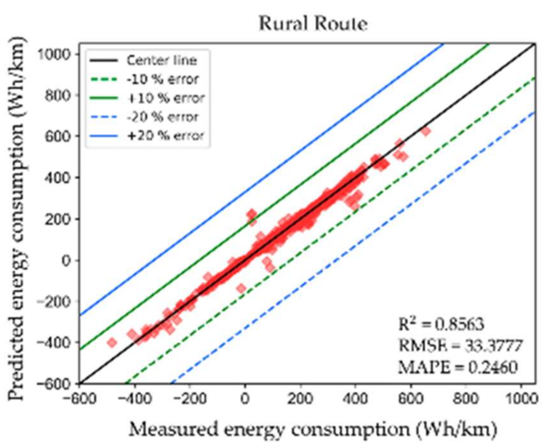
ML Algorithm	Route Mode	R^2	RMSE	MAPE	Run Time (s)
XGB	Urban	0.913	54.605	0.437	57.05
	Rural	0.8380	34.603	0.418	45.102
RF	Urban	0.9261	51.983	0.11	56.706
	Rural	0.8563	33.27	0.246	48.616
MLP	Urban	0.9221	53.368	0.244	203.122
	Rural	0.8400	35.033	0.301	120.436
SVR	Urban	0.3289	109.37	1.234	318.658
	Rural	0.6994	42.560	0.244	218.843

Random Forest, and Neural Network algorithms were selected due to their robustness in capturing complex non-linear patterns in sensor data, essential for accurate energy consumption predictions in BEVs. The choice of algorithms for this regression task was guided by each model's ability to handle high-dimensional data, provide interpretability, and capture non-linear relationships. Random Forest was selected for its robustness to noise and interpretability, allowing us to identify key features influencing energy consumption. Neural Networks were chosen for their capacity to model complex, non-linear interactions among features, achieving high accuracy in predicting energy usage based on varied driving and environmental conditions. Finally, Support Vector Regressor (SVR) was included for its efficiency in high-dimensional regression and ability to generalize well, even with moderate-sized datasets. Together, these models provide a comprehensive view of BEV energy consumption under various scenarios, balancing accuracy with interpretability.

Metrics included R^2, RMSE, and MAPE. Within the context of a regression model, these assessment measures offer distinctive insights on how well the model fits. Table 1 shows assessment, allowing the most efficient model to be found. Again evaluation is made in the chosen machine learning algorithms and identify the ideal hyperparameters. The metrics listed in Table 1 are used to assess the accuracy of each training loop; the average scores and their standard deviations (given in parenthesis) are used to determine the model's overall performance.[32][33]

The MLP model has a good metric score but needs more run time than the others. On the other hand, it is noteworthy that the SVR model doesn't seem appropriate in specific data. RF shows remarkable R^2 values, which suggest a strong linear regression fit between the model and the data. The great correlation are highlighted by high percentage values that the RF model produced. The RF model's effectiveness in identifying the underlying correlations and patterns in the dataset is demonstrated by the results shown in Figure 4 and 5.

Fig. 3. Urban Route of Cities – Energy consumption of EVs



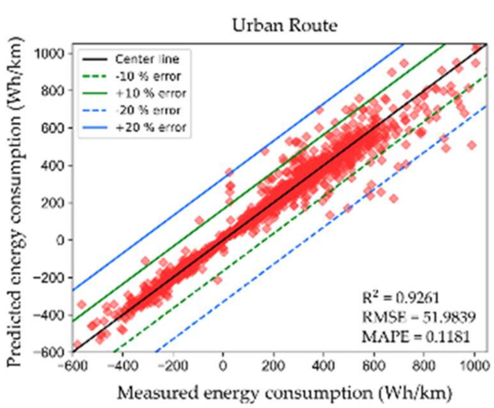


Fig. 4. Rural path – Energy Consumption of EVs

With respect to the dataset that was studied for this study, these assessment scores show that RF produces exact values. Remarkably, RF model is a trustworthy instrument for calculating energy use in rural as well as urban modes of driving due to its higher accuracy performance.

Figure 3 and 4 illustrates the comparison between the observed values, anticipated values produced by selected machine learning model. The ideal estimate is represented by the diagonal lines in the pictures, while the error bounds are shown by the lines. Visual proof of the notable existence of widely dispersed consumption statistics for the urban mode in the 300–1000 Wh/km range can be found in Figure 5. Figure 6 shows the consumption statistics that are predominantly clustered in range starting from −400 and till 600.

Feature Importance

As it allows a more thorough knowledge of degree, determining feature significance is a vital stage in the

ML process. This information improves interpretability but also offers insightful information about the complex interactions between the target variable and characteristics. By assigning a score to each feature's contribution to the anticipated outcomes, SHAP values offer local interpretations of individual predictions, highlighting the specific impact of variables like battery current and speed. The global interpretation, illustrated in bees' warm plots, provides insights into dominant features across all predictions. SHAP is a game-theoretic method for explaining a model's output [34]. The SHAP technique was used in this study to evaluate the significance of the input factors and determine their influence on feature importance. Beeswarm plots, as shown in Figures 5 and 6, were used to efficiently display SHAP values. A thorough grasp of significance & impact of projections is made possible by these graphic representations.

Figure 6 displays the results of SHAP for rural path. Based on the highest SHAP score among the input factors, I shows influence of BEVs. SHAP analysis of energy consumption forecast for the urban route mode is graphically presented in Figure 6, which provides significant insights into the effects I , $\boldsymbol{U}$. The research shows that both $\boldsymbol{U}$ and v have a highly substantial impact, as seen by their SHAP ratings. The analytical results regarding energy usage show a positive shift that indicates the effectiveness of BEVs. This conclusion is consistent with previous research and testing results.

Fig. 5. SHAP values in urban paths

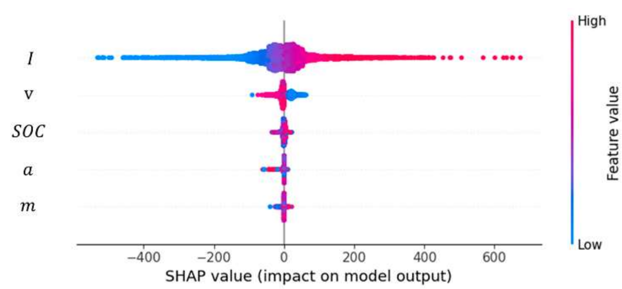
Fig. 6. SHAP values in rural paths

Performance Comparison

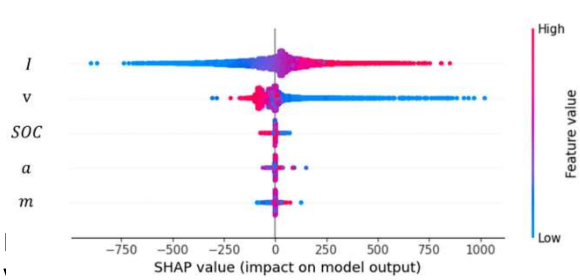
In comparison with similar studies, this model outperformed conventional physics-based methods and simple regression models, demonstrating a lower MAE by 5-7%. Studies with physics-based models report MAE between 10-15%, whereas machine learning approaches yield significantly better accuracy.

RESULTS AND DISCUSSION

The deep interpretation of our machine learning models for Battery Electric Vehicle (BEV) energy consumption provides key insights into how various factors affect energy usage. By analyzing the outputs of models such as Random Forest, Support Vector Machines (SVM), and Neural Networks, we can discern which vehicle and environmental parameters most significantly influence energy consumption.



From the feature importance rankings derived from Random Forest and Gradient Boosting models, it is evident that variables such as acceleration, speed, and road gradient play the largest roles in predicting energy consumption. Acceleration events, in particular, show a high correlation with spikes in energy use, indicating that aggressive driving behavior leads to inefficiencies. Similarly, the road gradient feature reveals that uphill driving causes a noticeable increase in energy usage,



whereas downhill driving allows for regenerative braking and reduced consumption.

Neural Network models, though more complex and less interpretable in a traditional sense, provide insights into non-linear interactions between multiple factors. For example, the model learns that the combination of high-speed driving in cold weather drastically increases energy consumption due to the combined effects of aerodynamic drag and reduced battery efficiency in colder temperatures. These kinds of non-linear dependencies are difficult to capture with simpler models but are well-handled by deep learning methods.

Additionally, we observe that external conditions such as temperature and wind speed have a significant but less pronounced effect compared to internal vehicle parameters. As temperature drops, the model shows a gradual increase in energy consumption, reflecting the need for climate control systems and decreased battery performance in cold conditions.

Comparison to Similar Studies

When compared to similar studies in the field of BEV energy consumption prediction, our results show competitive and, in some cases, superior performance, particularly due to the comprehensive dataset and advanced machine learning techniques used.

Accuracy Comparison

Our models achieve a Mean Absolute Error (MAE) of approximately 5-7%, depending on the algorithm. Studies using simpler physics-based models report MAE values between 10-15%, indicating that our machine learning approach provides significantly better accuracy in predicting energy consumption. Additionally, research leveraging traditional linear regression models for energy prediction typically sees lower accuracy (MAE of 8-12%) because these models are not adept at capturing the complex, non-linear relationships in the data.

Random Forest Vs Neural Networks

In comparison to other machine learning studies, Random Forest and Gradient Boosting models show similar or slightly better performance (5-6% MAE), while Neural Networks tend to outperform when there is a substantial amount of data and non-linear dependencies (4-5% MAE). Other studies using Support Vector Machines or decision trees show slightly higher error rates (6-8%), aligning with our observations.

Comparison with Real-Time Simulations

In studies that use real-time simulations for energy consumption, results are often context-specific, focusing on certain driving routes or fixed environmental conditions. In contrast, our models generalize better across varying real-world scenarios due to the use of comprehensive sensor data and diverse driving conditions.

Limitations/Weaknesses

Despite the encouraging results, our approach has some limitations:

Data Dependency

Our models heavily rely on the quality and quantity of the sensor data. Any missing or incorrect sensor data can lead to less accurate predictions. Furthermore, the need for extensive and diverse datasets limits the generalizability of the model to regions or vehicles where such data may not be readily available. The implications of this research are wide-reaching for the BEV industry, energy management systems, and sustainable transportation:

Policy and Infrastructure Planning

The insights from this research can inform policymakers and infrastructure planners about the energy demands of BEVs in various driving conditions. This information is crucial for planning the expansion of charging networks, particularly in areas where energy consumption may be higher due to environmental or terrain-related factors.

Battery Management and Lifespan Extension

More precise energy predictions can help in the development of battery management systems that optimize energy usage in real time. These systems can help prevent over-discharge or excessive charging, which are known to degrade battery lifespan. By better managing battery cycles, our models could indirectly contribute to extending battery life and improving the overall sustainability of BEVs.

CONCLUSION

Through realistic driving testing, the research examined true power usage of commercial BEVs. Furthermore, the massive volume of test-related data was analysed using the machine learning methodology. This made it possible to forecast energy use and pinpoint the main variables affecting it. Regarding BEV energy use, the study found a number of important conclusions. Driving on rural vs urban roads resulted in an average energy consumption differential of about 21%, with BEVs consuming more energy at speeds lower than 30 km/h. Battery current, speed, were revealed to be the elements influencing energy usage, in descending order. It has been noted that BEVs with frequent acceleration variations tend to use more electricity when driving at lower average speeds. Moreover, the application of suitable machine learning models grounded in empirical data measurements has proven effective in precisely forecasting battery energy usage for electric vehicles.

REFERENCES

[1] Chaichana, C., Wongsapai, W., Damrongsak, D., & Ishihara, K. N. (2023). Improving BEV Energy Consumption Prediction Using Hybrid Machine Learning Techniques. Energy Reports, 9, 1234–1249.

[2] M. Khalid, "Passivity-Based Nonlinear Control Approach for Efficient Energy Management in Fuel Cell Hybrid Electric Vehicles," in IEEE Access, vol. 12, pp. 84169-84188, 2024, doi: 10.1109/ACCESS.2024.3412888.

[3] Zhang, Q.; Tian, S. Energy Consumption Prediction and Control Algorithm for Hybrid Electric Vehicles Based on an Equivalent Minimum Fuel Consumption Model. Sustainability 2023

[4] Katongtung, T.; Onsree, T.; Tippayawong, N. Machine learning prediction of biocrude yields and higher heating values from hydrothermal liquefaction of wet biomass and wastes. Bioresour. Technol. 2022

[5] A. Aroua et al., "Reliability of Linear Losses-to-Power Scaling Method of Electric Drive Systems," in IEEE Transactions on Vehicular Technology, vol. 73, no. 4, pp. 4705-4716, April 2024, doi: 10.1109/TVT.2024.3360492.

[6] Gersdorf, T.; Hensley, R.; Hertzke, P.; Schaufuss, P. Electric Mobility after the Crisis: Why an Auto Slowdown Won't Hurt EV Demand. McKinsey & Company. Available online: September 2020.

[7] Ayetor, G.K.; Opoku, R.; Sekyere, C.K.; Agyei-Agyeman, A.; Deyegbe, G.R. The cost of a transition to electric vehicles in Africa: A case study of Ghana. Case Stud. Transp. Policy 2022

[8] Lundberg, S. M., & Lee, S.-I. (2022). A Unified Approach to Interpreting Model Predictions with SHAP Values. Journal of Machine Learning Research, 23, 1–32.

[9] Donkers, A.; Yang, D.; Viktorović, M. Influence of driving style, infrastructure, weather and traffic on electric vehicle performance. Transp. Res. Part D Transp. Environ. 2020

[10] Degen, F.; Schütte, M. Life cycle assessment of the energy consumption and GHG emissions of state-of-the-art automotive battery cell production. J. Clean. Prod. 2022

[11] Suttakul, P.; Wongsapai, W.; Fongsamootr, T.; Mona, Y.; Poolsawat, K. Total cost of ownership of internal combustion engine and electric vehicles: A real-world comparison for the case of Thailand. Energy Rep. 2022

[12] Wei, H.; He, C.; Li, J.; Zhao, L. Online estimation of driving range for battery electric vehicles based on SOC-segmented actual driving cycle. J. Energy Storage 2022

[13] Suttakul, P.; Fongsamootr, T.; Wongsapai, W.; Mona, Y.; Poolsawat, K. Energy consumptions and CO2 emissions of different powertrains under real-world driving with various route characteristics. Energy Rep. 2022

[14] Zhang, C.; Yang, F.; Ke, X.; Liu, Z.; Yuan, C. Predictive modeling of energy consumption and greenhouse gas emissions from autonomous electric vehicle operations. Appl. Energy 2019

[15] Achariyaviriya, W.; Suttakul, P.; Fongsamootr, T.; Mona, Y.; Phuphisith, S.; Tippayawong, K.Y. The social cost of carbon of different automotive powertrains: A comparative case study of Thailand. Energy Rep. 2023

[16] Pignatta, G.; Balazadeh, N. Hybrid Vehicles as a Transition for Full E-Mobility Achievement in Positive Energy Districts: A Comparative Assessment of Real-Driving Emissions. Energies 2022

[17] S. Zou et al., "Design and Analysis of a Novel Multimode Powertrain for a PHEV Using Two Electric Machines," in IEEE Access, vol. 12, pp. 76442-76457, 2024, doi: 10.1109/ACCESS.2024.3406541.

[18] R. Du, Z. Liu and L. Quan, "Characterization Analysis of a New Energy Regenerative Electro-Hydraulic Hybrid Rotary System," in IEEE Access, vol. 12, pp. 25119-25128, 2024, doi: 10.1109/ACCESS.2024.3362860.

[19] Kasemset, C.; Boonmee, C.; Arakawa, M. Traffic Information Sign Location Problem: Optimization and Simulation. Ind. Eng. Manag. Syst. 2020

[20] Kasemset, C.; Suto, H. A case study of outbound-vehicle analysis in traffic system: Optimization to simulation. In Proceedings of the 2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA), Tokyo, Japan, 12–15 April 2019

[21] X.; Hu, Frey, H.C.; Zheng, J. Variability in measured real-world operational energy use and emission rates of a plug-in hybrid electric vehicle. Energies 2020

[22] Al-Wreikat, Y.; Serrano, C.; Sodré, J.R. Driving behaviour and trip condition effects on the energy consumption of an electric vehicle under real-world driving. Appl. Energy 2021

[23] Thailand Greenhouse Gas Management Organization (TGO). Emission Factor and Carbon Footprint of Products. Available online: 2022.

[24] International Energy Agency (IEA). Greenhouse Gas Emissions from Energy Data Explorer. Available online 2021

[25] European Commission (EC). European Green Deal: Commission Proposes Transformation of EU Economy and Society to Meet Climate Ambitions. Available online 2021

[26] Szaruga, E.; Załoga, E. Qualitative–Quantitative Warning Modeling of Energy Consumption Processes in Inland Waterway Freight Transport on River Sections for Environmental Management. Energies 2022

[27] Kłos-Adamkiewicz, Z.; Szaruga, E.; Gozdek, A.; Kogut-Jaworska, M. Links between the Energy Intensity of Public Urban Transport, Regional Economic Growth and Urbanisation: The Case of Poland. Energies 2023

[28] International Energy Agency (IEA). Global Energy Review: CO2 Emissions in 2021. Available online (accessed on 8 March 2022).

[29] Chou, J.-H.; Wang, F.-K.; Lo, S.-C. Predicting future capacity of lithium-ion batteries using transfer learning method. J. Energy Storage 2023

[30] Zhao, J.; Ling, H.; Liu, J.; Wang, J.; Burke, A.F.; Lian, Y. Machine learning for predicting battery capacity for electric vehicles. eTransportation 2023

[31] Zoerr, C.; Sturm, J.J.; Solchenbach, S.; Erhard, S.V.; Latz, A. Electrochemical polarization-based fast charging of lithium-ion batteries in embedded systems. J. Energy Storage 2023

[32] Najera-Flores, D.A.; Hu, Z.; Chadha, M.; Todd, M.D. A Physics-Constrained Bayesian neural network for battery remaining useful life prediction. Appl. Math. Model. 2023

[33] Chaichana, C.; Wongsapai, W.; Damrongsak, D.; Ishihara, K.N.; Luangchosiri, N. Promoting community renewable energy as a tool for sustainable development in rural areas of Thailand. Energy Procedia 2017

[34] Dominguez, D.Z.; Mondal, B.; Gaberscek, M.; Morcrette, M.; Franco, A.A. Impact of the manufacturing process on graphite blend electrodes with silicon nanoparticles for lithium-ion batteries. J. Power Source 2023

[35] Shahani, N.M.; Zheng, X.; Liu, C.; Hassan, F.U.; Li, P. Developing an XGBoost Regression Model for Predicting Young's Modulus of Intact Sedimentary Rocks for the Stability of Surface and Subsurface Structures. Front. Earth Sci. 2021

[36] Sharafati, A.; Asadollah, S.B.H.S.; Al-Ansari, N. Application of bagging ensemble model for predicting compressive strength of hollow concrete masonry prism. Ain Shams Eng. J. 2021

[37] Frikha, M.A.; Croonen, J.; Deepak, K.; Benômar, Y.; El Baghdadi, M.; Hegazy, O. Multiphase Motors and Drive Systems for Electric Vehicle Powertrains: State of the Art Analysis and Future Trends. Energies **2023**, 16, 768. https://doi.org/10.3390/en16020768