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2024년 2월

석사학위 논문

Development of a Battery Consumption Prediction Model for Micro Electric Vehicles in Real-World Driving Conditions

조선대학교 대학원

산업공학과

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2024년 2월 23일

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2023년 10월

조선대학교 대학원

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최 인 규

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초소형 전기차(MEV)는 전기차(EV)의 소형 버전으로, 퍼스트 마일 및 라스트 마일 솔루션 그리고 운송 서비스 분야에서 주목을 받고 있다. 하지만 상대적으로 제한된 배터리 용량과 긴 충전 시간으로 인해 운전자와 OEM사 모두에게 배터리 사용량은 주요 관심사이다. 본 연구에서는 대규모의 과거 주행 데이터를 활용해 초소형 전기차의 배터리 사용량을 예측하는 새로운 프레임워크를 소개하고자 한다. 제안된 프레임워크는 두 단계로 구성된다. 첫 번째 단계에서는 다양한 주행 특징을 반영한 배터리 사용량 예측 모델을 개발한다. 그리고 주행 거리와 같은 단일 입력 변수를 활용하여 주행 특징을 추출할 수 있는 주행 프로파일 추출기를 개발한다. 두 번째 단계에서는 추출기와 예측 모델을 통합하여 간소화된 단일 입력 예측 모델을 개발한다. 또한, 부트스트랩 기법을 사용하여 예측 구간을 계산한다. 이러한 접근 방식은 실주행 환경에 적용 가능하며, 예측모델 구현을 단순화할 수 있다. 프레임워크의 성능은 실제 주행 데이터를 사용하여 검증되며, 배터리 잔량에 따른 주행 거리 및 MEV 가용도 예측과 같은 실제 적용 사례를 통해 입증된다. 제안한 프레임워크는 MEV 사용자들이 차량을 효율적으로 관리할 수 있는 기능을 제공한다.

ABSTRACT

Development of a Battery Consumption Prediction Model for Micro Electric Vehicles in Real-World Driving Conditions

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Micro Electric Vehicles (MEVs), compact versions of standard electric vehicles (EVs), are increasingly popular for first- and last-mile transportation and delivery services. For both drivers and mobility companies, battery consumption is a major concern because of their comparatively limited battery capacity and long recharge times. This study introduces a novel prediction framework for MEV battery consumption, employing large-scale historical driving data. The proposed framework consists of two stages. The first involves developing a battery consumption prediction model that incorporates a wide range of driving features. Simultaneously, a driving profile extractor is developed that can generate these driving features from a single input, such as the driving distance. The second stage integrates the extractor with the prediction model, resulting in a streamlined single-input prediction model. Additionally, a bootstrap-based inference method is introduced for calculating prediction intervals. Designed for real-world applicability, this approach simplifies the implementation of the predictive model. The framework's performance is validated using real-world driving data and illustrated through practical applications, including the prediction of driving distance and MEV availability based on remaining battery capacity. It provides MEV users with essential tools for efficient vehicle management

I. INTRODUCTION

Micro electric vehicles (MEVs) have recently received significant attention as a promising solution for first- and last-mile public transportation solutions due to their mobility and eco-friendly attributes [1,2,3,4]. The global MEV market, according to [5], is anticipated to experience significant expansion, with an annual growth rate of 12.7%, and it has the potential to reach 22.1 billion dollars by 2029. However, MEVs encounter several challenges. Currently, MEVs have a limited range of approximately 50 miles per charge, whereas conventional full electric vehicles (EVs) can travel over 200 miles. In addition, MEVs lack the capability for fast charging, requiring a minimum of 3.5 hours to fully charge. Furthermore, compatibility problems with regular EV chargers lead to a restricted charging infrastructure. As a result of these limitations, MEV drivers may experience greater concern for battery consumption. Such challenges are crucial for stakeholders, including vehicle manufacturers, government bodies, and drivers, influencing decisions from the purchase to the daily operation and management of MEVs. Consequently, the precise prediction of battery consumption in real-world driving conditions is vital for optimizing the efficiency of MEVs.

In the literature, several studies have introduced diverse approaches for predicting battery consumption in EVs. Previous studies typically classified the data into two types: static, referring to offline data, and dynamic, referring to real-time data. The data can be further categorized based on the collection environment into experimental and field data, resulting in four distinct research topics within these categories. For static data analysis, traditional statistical methods, including Robust nonlinear regression [6], mixed-effects linear regression [7,8], and Multiple Linear Regression (MLR) [9], have been utilized alongside machine learning techniques such as extreme gradient boosting (XGBoost) [10,11] support vector machine (SVM) [12], artificial neural network (ANN) [13], Deep neural network (DNN) [14,15], and k-nearest neighbors (KNN) [16]. For example, Liu et al.[7] developed a mixed-effects linear regression model for energy consumption prediction, considering driving habits under various road and traffic conditions. Cauwer et al.[9] introduced an MLR-based model, correlating kinematic parameters with energy consumption. Zhang et al.[10] proposed an XGBoost-based framework, integrating driving condition predictions with energy consumption factors. In the laboratory setting, Antón et al.[12] estimated the battery's state of charge (SOC) using variables like temperature and voltage, while Shrivastava et al.[14] compared SOE estimation methods using DNN and SVR for EV energy management efficiency. Li et al.[16], addressing the rise of electric buses, suggested a framework for battery capacity prediction and dynamic scheduling management.

For dynamic data analysis, DNN [17], Convolution Neural Network (CNN) [18,19,20], Recurrent Neural Network (RNN) [21,22], and Long Short-Term Memory (LSTM) [23,24,25] models have been adopted. Field data studies include Eissa et al.[20], who predicted the remaining driving range by forecasting user speed profiles, and Xiaogang et al.[23], who used LSTM for SOC prediction, focusing on aging and thermoelectric characteristics. Laboratory studies by Tian et al.[17] and [25] demonstrated SOC estimation methods using short-term charging data and a combination of LSTM with adaptive cubic Kalman filter (ACKF), respectively.

Although numerous studies have been suggested to predict battery consumption using different data types, a common drawback is their dependence on a large number of predictor variables. The complexity of current prediction models limits their practicality for general use. Additionally, their validation often relies on limited datasets, confining their applicability to controlled, experimental settings. This situation highlights a critical need for more adaptable and intuitive models suitable for real-world contexts beyond laboratory confines.

In this research, we introduce a novel two-stage battery consumption prediction model designed for Micro Electric Vehicles (MEVs) operating in real-world driving conditions. The first stage involves developing a prediction model that utilizes a comprehensive set of driving features. Simultaneously, we develop a driving profile extractor capable of predicting these features from just a single variable, such as driving distance. In the second stage, we integrate this extractor with the prediction model, enabling precise battery consumption predictions using a single input. Furthermore, we employ a bootstrap-based inference method for calculating prediction intervals. This model aims to significantly simplify the predictive process, overcoming a key limitation of traditional battery consumption prediction models while ensuring high accuracy. The major contributions of this study are threefold. First, the model's simplicity is emphasized by its usage of only a single input variable, which improves its intuitiveness and user-friendliness. This approach reduces the complexity typically associated with predictive variables, making the model more comprehensible and user-friendly. Second, the proposed model provides flexibility through the customizable feature extractor, which can be tailored to individual users' driving styles and objectives. This adaptability allows for personalized predictions that meet the diverse needs of various users. Third, the prediction capability is enhanced by introducing bootstrap-based prediction intervals. This addition provides a quantifiable measure of prediction uncertainty, offering drivers valuable information to make data-driven decisions.

The structure of this study is as follows: Section 2 presents a comprehensive outline and process for our battery consumption prediction framework. Section 3 provides a comprehensive explanation of the specific processes and methodology used in the proposed framework. The process involves identifying the driving characteristics that affect battery consumption and integrating them into the predictive model. Section 4 presents real-world examples where our proposed framework is applied, demonstrating its effectiveness. Lastly, Section 5 concludes our study by highlighting our main conclusions and outlining potential directions for further research in this area.

II. OVERVIEW OF PROPOSED FRAMEWORK

In this section, we describe the framework for our battery consumption prediction model, as shown in Figure 1. The process begins with a critical phase of data processing and feature extraction, essential for preparing the modeling dataset. This initial phase involves segmenting driving data and extracting relevant features that affect battery consumption using real-time driving data. The analysis provides insights into the effects of driving patterns, vehicular kinematics, and environmental factors on battery consumption, with more details discussed in Section 3.1.

The first stage of the framework focuses on developing a Multi-Feature Prediction Model (MFPM), which integrates the extracted features to accurately reflect the vehicle’s and driver's characteristics. This stage includes optimizing hyperparameters through k-fold cross-validation and grid search methods, detailed in Section 3.2. However, the MFPM relies on numerous predictive variables, which may not be readily available prior to driving, posing a challenge for practical implementation. In order to address this issue, we introduce the Driving Profile Extractor (DPE). The DPE is capable of deriving prediction features from historical data based on a single driving feature, such as driving distance. The details are explained in Section 3.3.

The second stage integrates the DPE's output with the MFPM, creating a unified Single Feature Prediction Model (SFPM). The SFPM combines the advantages of the DPE and MFPM, providing a user-friendly interface and improved prediction accuracy. The details of this stage of the framework are explained in Section 3.4. In addition, the proposed model employs bootstrap-based prediction intervals to quantify uncertainty in the predictions, ensuring a reliable assessment. This approach is further analyzed in Section 3.5.

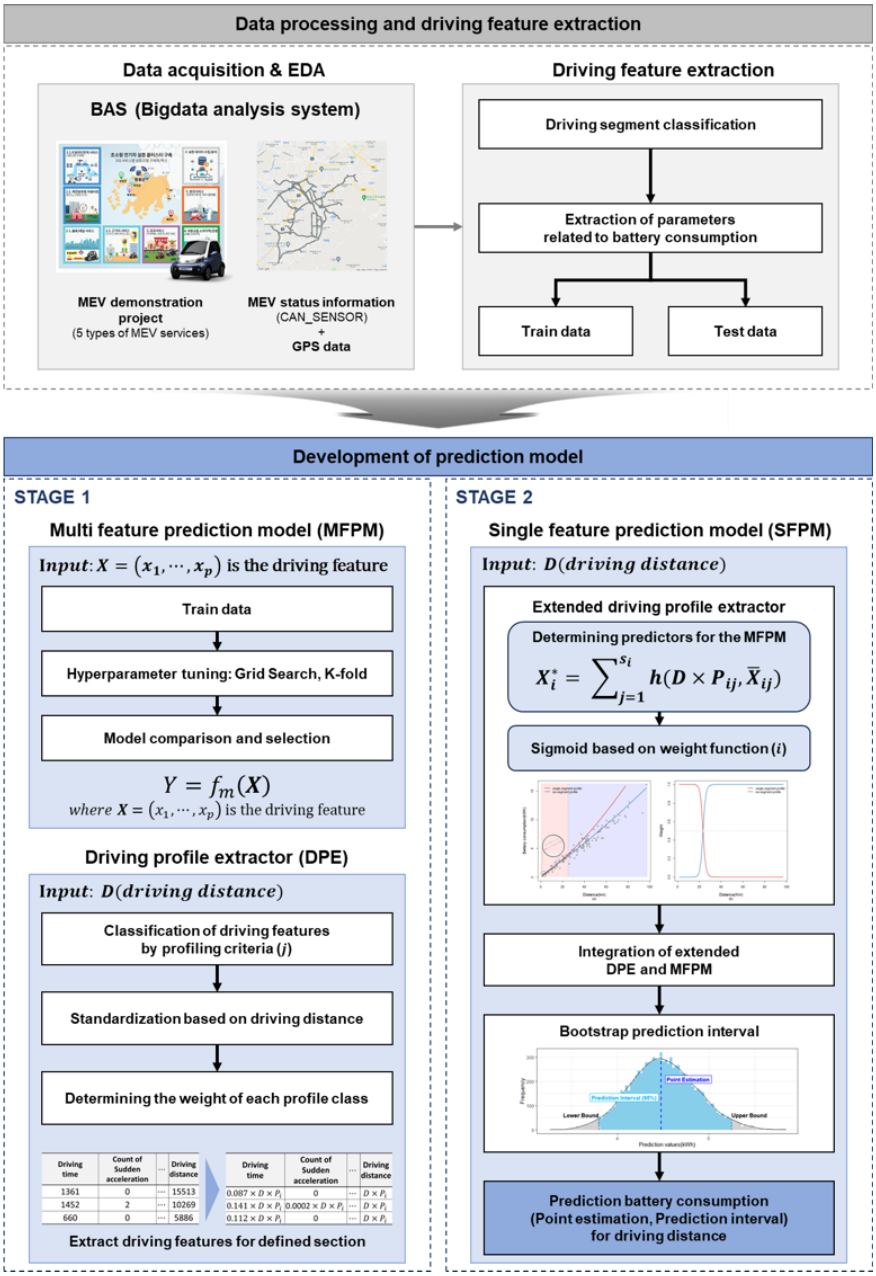

Figure 1 : Proposed framework for predicting battery consumption in micro electric vehicles

III. DEVELOPMENT OF PREDICTION MODEL

A. Identification of Factors Related to Battery Consumption

We obtained research data from KATECH's (Korea Automotive Research Institute) E-mobility research center’s MEV Big Data platform. We conducted an analysis of data obtained from four distinct MEV models that are currently in operation in the Republic of Korea. The dataset, which includes comprehensive driving information and maintenance records for MEVs, was transmitted wirelessly to the Big Data platform. An example driving trajectory for these MEVs is illustrated in Figure 2.

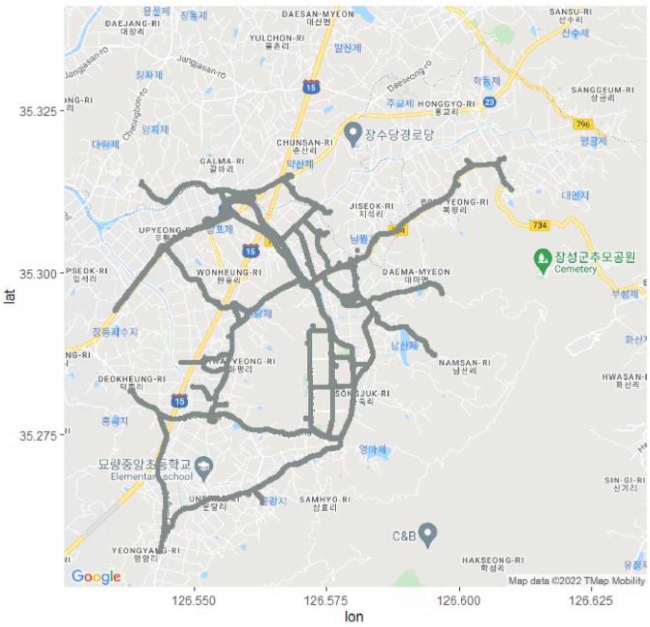

Figure 2 : Visualization of micro electric vehicle (MEV) driving data

The selected micro electric vehicles (MEVs), as outlined in Table 1, require a minimum of 3.5 hours to fully charge and provide a driving range of roughly 100 km. Data collection occurred every second from July 2020 to March 2023, resulting in a comprehensive dataset with 34 variables. These variables, including time, vehicle position, acceleration, angular velocity sensors, and State of Charge (SOC), are detailed in Table 2. For our analysis, we selected data from 37 out of the 148 MEVs that provided stable and reliable data.

In this research, the initial phase in handling driving data is to filter out any data with GPS inaccuracies, noise, or other anomalies to ensure data integrity. After the first filtering, we applied South Korea's traffic regulations, which define any stop exceeding more than 5 minutes as 'parking'. Based on this rule, we segmented the driving data into individual trips. In this section, based on these segments, we processed each segment of driving data into driving features. These driving features represent the unique characteristics of battery consumption for each individual trip.

Parameters	Values			
Brand	Semisisco	Semisisco	Masta	Renault
Model	D2	D2C	VAN	Twizy
Battery capacity	17 kWh	17.4 kWh	72 V	129 Ah
Maximum power	15 kW	15 kW	7.5 kW	12.6 kW
weight	660 kg	720 kg	613 kg	475 kg
Maximum speed	80 km/h	80 km/h	80 km/h	80 km/h
Range	150 km	101 km	120 km	100 km/h
Charging time	6 h	6 h	3.5 h	3.5 h

Table 1 : Specification of Micro Electric Vehicles used in the study

No.	sent_on	carname	carnumber	…	longitude	latitude	pitch	speed	can_rpm	can_soc
1	2020-12-09 0:00:00	VAN	90 보 0232	…	126.58	35.3	8.88	0	0	9.96
2	2020-12-09 0:00:01	VAN	90 보 0232	…	126.58	35.3	8.89	0	0	9.96
3	2020-12-09 0:00:02	VAN	90 보 0232	…	126.58	35.3	8.88	0	0	9.96
4	2020-12-09 0:00:03	VAN	90 보 0232	…	126.58	35.3	8.87	0	0	9.96
…	…	…	…	…	…	…	…	…	…	…
86399	2020-12-09 23:59:58	VAN	90 보 0232	…	126.57	35.3	5.71	0	0	7.2
86400	2020-12-09 23:59:59	VAN	90 보 0232	…	126.57	35.3	5.71	0	0	7.2

Table 2 : Examples of driving data from micro electric vehicles

According to earlier studies [8,9,26,27,28,29,30,31,32,33,34], driving patterns and kinetic properties have an impact on the battery consumption in MEVs. Driving behaviors, such as rapid acceleration and deceleration, have a strong correlation with fluctuations in kinetic energy. According to a study by [33], prediction accuracy can be improved by including driving patterns in energy consumption models. Kinetic characteristics, such as changes in altitude, changes in speed, and idle times, also have a significant impact on battery consumption. Uphill driving requires a greater amount of energy, whereas downhill driving can recover or save energy by utilizing regenerative braking systems in vehicles. Al et al. (2021) [31] showed that a road gradient of 3% leads to a 50% increase in battery consumption, whereas a gradient of -3% results in a decrease of 80% compared to flat roads. Research conducted by [35,36] demonstrates that idling, which refers to the energy use of a vehicle while it is parked, also has an impact on overall battery consumption.

To develop our prediction model, we initially utilize variables previously identified in studies [8,31,32,33,34,35]. Furthermore, we incorporate new variables that reflect aggressive driving behaviors leading to increased battery consumption and variations in elevation. These additional variables, based on criteria established by the Korea Road Traffic Authority, include rapid accelerations, sudden stops, and occurrences of exceeding the speed limit. The detailed definitions and standards for these behaviors are presented in Table 3.

Vehicle states	Definition
Acceleration	If the accelerator pedal is pressed (one case within 3 seconds, processing separately after 4 seconds)
Deceleration	If the Brake pedal is pressed (one case within 3 seconds, treated separately after 4 seconds)
Violation_acceleration	When driving more than 20 km/h than the road speed limit (one case within 3 seconds, separately processed after 4 seconds)
Sudden_acceleration	Accelerating over 8km/h per second at speeds greater than 6.0 km/h
Sudden_deceleration	Decelerating over 14km/h per second at speeds greater than 6.0 km/h (one case within 1 seconds, processing separately after 2 seconds)
Sudden_stop	If the speed becomes less than 5.0 km/h after deceleration of more than 14 km/h per second

Table 3 : Criteria for aggressive driving behaviors

In this study, we employ the variables relating to the influence of uphill and downhill driving on battery consumption introduced in the literature [29,31,32]. Accurately assessing the vehicle's inclination is crucial in this context. We use the pitch value calculated from the driving data to measure this inclination. A pitch value of 0 indicates that the vehicle is driving on a flat road. Positive values indicate an upward tilt of the vehicle, and negative values indicate a downward tilt. Although the pitch (ρ) value is already included in the collected data, it undergoes further refinement for enhanced accuracy. This refinement involves calculating a corrected pitch (ρ_c) using accelerometer data (AcX, AcY, and AcZ), as described in Equation 1.

$$\rho_c = arctan\left(-\frac{A_x}{\sqrt{A_y^2 + A_z^2}}\right) \tag{1}$$

$$D_h = \frac{D_{10}}{tan(90° - \rho_m)} \times \frac{180°}{\pi} \tag{2}$$

In order to enhance precision, we calculate the average of the initial pitch (ρ) and the calculated pitch (ρ_c) to obtain a corrected pitch (ρ_m) value. We chose to measure the adjusted pitch value (ρ_m) every 10 seconds, allowing us to estimate the vehicle's average tilt. The vehicle's tilt is categorized into four types according to the degree of steepness: less than -3%, between -3% and 0%, between 0% and 3%, and more than 3%. Subsequently, we count the frequency of each pitch type for each driving segment.

In addition, we calculate the altitude change for each 10-second interval. This calculation uses the driving distance (D_{10}), the average ρ_m value, and trigonometric ratios, as outlined in Equation 2. By aggregating these altitude changes across all pitch types, we determine the total elevation change for the entire driving duration. This provides us with altitude changes caused by the vehicle's tilt, providing valuable information on its impact on battery consumption.

The initial phase of the study involved collecting an extensive dataset of time-series driving data from 37 Micro Electric Vehicles (MEVs), covering a broad range of variables across a continuous time frame. The original dataset comprised a total of 481,334,400 records. During the subsequent data processing stage, which included segmentation and feature extraction, the dataset was refined to focus on the most relevant variables for battery consumption prediction models. This process resulted in the selection of 27 key driving features, reducing the total number of records to 18,965. These features and their basic statistical properties are detailed in Table 4.

No.	Parameter	Mean	Sd
1	Driving time(s)	1575.65	1376.74
2	Count of sudden accelerations	1.38	2.83
3	Count of SuddenDeaccelerations	0.05	0.24
4	Count of Sudden Stops	0.03	0.18
5	Count of Accelerations	77.68	68.47
6	Count of Deaccelerations	79.5	70.89
7	Count ofCruiseDrives	30.78	29.89
8	Count of Speeding Incidents	57.02	93.05
9	Count of Idling Incidens	586.46	610.78
10	Count of speed intervals 0-10km/h	112.01	144.28
11	Count of speed intervals 10-20km/h	237.05	307
12	Count of speed intervals 20-30km/h	213.72	213.66
13	Count of speed intervals 30-40km/h	140.4	142.93
14	Count of speed intervals 40-50km/h	107.11	148.88
15	Count of speed intervals 50-60km/h	92.89	161.75
16	Count of speed intervals 60-70km/h	69.03	123.74
17	Count of speed intervals 70-80km/h	3.08	9.91
18	Count of Drives on roads with gradient less steep Than -3%	83.76	78.12
19	Count of Drives on roads with gradient 0 to -3%	390.5	384.65
20	Count of Drives on roads with gradient 0 to 3%	6.35	9.71
21	Count of Drives on roads with gradient stepperThan 3%	39.62	42.76
22	Driving Distance on roads with gradient less steep Than -3%	1861.69	1861.95
23	Driving Distance on roads with gradient 0 to -3%	2900.06	2669.97
24	Driving Distance on roads with gradient 0 to 3%	156.08	242.78
25	Driving Distance on roads with gradient stepper Than 3%	610.62	699.09
26	Driving Distance(km)	8.27	7.34
27	Using_battery	1.21	1.08

Table 4 : Driving feature related to battery consumption

B. Multi-Feature Prediction Model (MFPM)

In previous research, battery consumption prediction models have generally employed methods like Multiple Linear Regression (MLR), Support Vector Regression (SVR), XGBoost, and Deep Neural Networks (DNN). MLR establishes a relationship between multiple independent variables and one dependent variable, effectively quantifying their correlations [9,37]. SVR, based on the Vapnik-Chervonenkis (VC) theory, is a machine learning algorithm known for its unique approach to handling errors; it does not penalize errors within a certain threshold. This characteristic becomes particularly beneficial as the input data dimensionality increases, helping to avoid or limit function underestimation [37,38]. XGBoost is a type of ensemble machine learning model that connects decision trees. This approach is based on the concept of iteratively improving the model by each subsequent tree addressing the limitations of the previous ones. XGBoost is known for its efficient learning abilities and accurate predictions, which are achieved by optimizing the loss function's gradient instead of modifying data weights. This algorithm also stands out for its parallel processing capability, as highlighted in previous studies [10,11,39]. A deep neural network (DNN), which is a sort of deep learning model, excels at acquiring intricate patterns by using its several hidden layers. Its hierarchical learning approach enables each layer to progressively refine the solution to the problem at hand. This method is especially effective for handling multi-dimensional data and complex challenges, making DNN a powerful tool for prediction tasks [14,15].

For this study, we applied four different methods to develop models that accurately predict battery consumption in Micro Electric Vehicles (MEVs): Multiple

MLR		SVR		XGBoost		DNN	
k-fold	5	k-fold	5	k-fold	5	layer	3~5
		sigma	0.1e-7~0.1e9	maxdepth	3~5	node	16~128
		cost	0~0.1e9	eta	0.02~1	droupout	0~0.2
				gamma	0~0.2	batch	8~64
				subsample	0.6~1	epoch	~200
				colsample bytree	0.6~1	early stopping	10~20
				early stopping	10~20		

Table 5 : Hyperparameters for training MFPM models in each machine learning model

Linear Regression (MLR), Support Vector Regression (SVR), XGBoost, and Deep Neural Networks (DNN). The hyperparameters for each model were optimized through the use of k-fold cross-validation and grid search. K-fold cross-validation involves dividing the dataset into k subgroups of equal size. This allows each subset to be used as a test set in rotation, while the remaining data is used for training. The procedure is repeated k times, and the total model performance is calculated by the average of these iterations. Grid search was used together with k-fold cross-validation to systematically investigate and improve different combinations of hyperparameters. However, the approach for deep neural networks (DNN) needs adjustment due to two main problems: there wasn't enough driving data for training, which made overfitting more likely; and k-fold cross-validation made the computer work harder because it had to do so many retrainings. In order to address these problems, we created a training and test set that is utilized in particular for evaluating the performance of the DNN model instead of employing k-fold cross-validation. The hyperparameter settings utilized for each model are presented in Table 5. The Multi-Input Prediction Model (MIPM), which has been developed, incorporates driving features as inputs and is formulated as Equation 3.

$$Y = f_m(\mathbf{X}), where \mathbf{X} = (x_1, \cdots, x_p) \tag{3}$$

In this study, the performance of the Multiple Linear Regression (MLR), Support Vector Regression (SVR), XGBoost, and Deep Neural Networks (DNN) models was developed for a total of 37 vehicles. The hyperparameters of each model were optimized as previously mentioned. We evaluated their performance using a test set and three commonly used assessment metrics: the Root Mean Square Error (RMSE), the Mean Absolute Percentage Error (MAPE), and the Pearson Correlation Coefficient (PCC). In these metrics, 'n' denotes the sample size, y_i represents the actual battery consumption for an individual trip, and $\hat{y_i}$ indicates the predicted battery consumption by the model for that trip.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2} \tag{4}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y_i}|}{y_i} \tag{5}$$

$$PCC = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y_i} - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{y_i} - \bar{\hat{y}})}} \tag{6}$$

Figure 3 illustrates a comparison between the actual and predicted battery consumption for the 37 MEVs, evaluated for each prediction model. In this figure, black dots represent the training data, and blue dots indicate the test data. A stronger correlation between predicted values and actual values indicates a better fit for the model. In the training data, the XGBoost model outperformed other models, achieving the lowest RMSE of 0.1758 kWh and the lowest MAPE of 18.3764%. Additionally, it showed a high Pearson Correlation Coefficient (PCC) of 98.51%. On the other hand, for the test data, the SVR model performed better than other models. It achieved the lowest RMSE of 0.2781 kWh, MAPE of 22.8449%, and PCC of 96.03%. In conclusion, while the SVR model successfully explains the relationship between battery consumption and driving features at the Multi-Feature Prediction Model (MFPM) stage, it is not considered the final model. The Driving Profile Extractor (DPE) and MFPM are integrated at the Single Feature Prediction Model (SFPM) stage, which selects the final prediction model based on overall predictive performance.

		MLR	SVR	XGBoost	DNN
Train set	RMSE (kwh)	0.2523	0.2447	**0.1758**	0.2971
	MAPE (%)	23.3374	22.0901	**18.3764**	26.2803
	PCC (%)	96.88	97.1	**98.51**	95.65
Test set	RMSE (kwh)	0.3003	**0.2781**	0.289	0.3067
	MAPE (%)	24.0739	**22.8449**	23.2312	24.9197
	PCC (%)	95.41	**96.03**	95.67	95.11

Table 6 : Summary of MFPM performance using four machine learning models (Optimal scores in bold face)

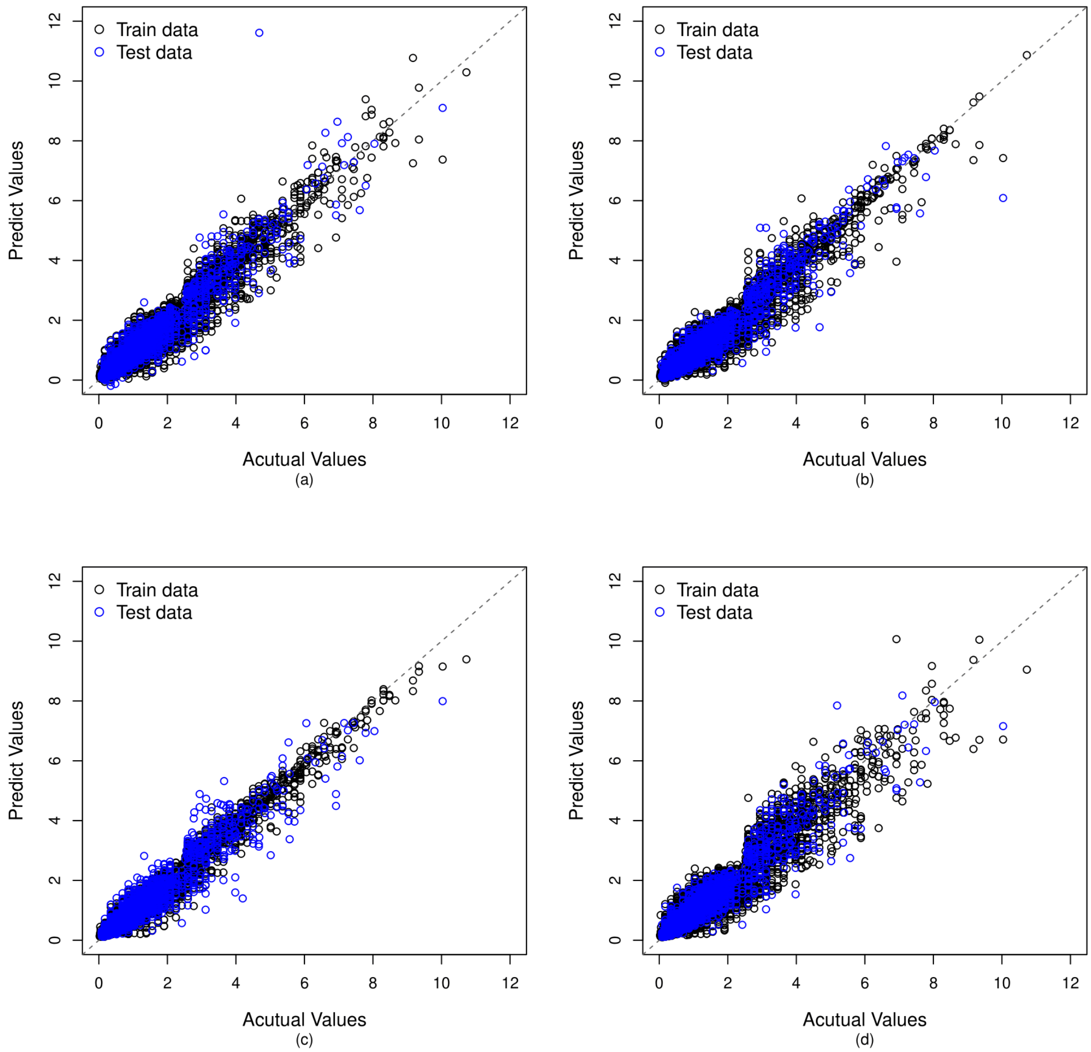

Figure 3 : Battery consumption prediction results for (a) MLR, (b) SVR, (c) XGBoost, and (d) DNN

C. Driving Profile Extractor (DPE)

In practical applications, conventional battery consumption prediction models, such as the Multi-Feature Prediction Model (MFPM), encounter challenges in selecting driving features as input variables. Although having a larger number of input variables can enhance the model's accuracy during training, this abundance becomes a disadvantage when the model is used for actual predictions. To address these challenges, prior studies have concentrated on forecasting forthcoming driving characteristics in order to generate more relevant input variables. Many of these studies employ machine learning and statistical methods. For instance, Li et al.[40] proposed a method combining the least squares support vector machine (LS-SVM) and back propagation neural network (BPNN). Zhang et al.[41] developed a technique using the Long Short-Term Memory (LSTM) model, incorporating variables like speed and acceleration to predict future driving conditions. In the statistical domain, methods like Markov-Chain Monte Carlo (MCMC) are often used to predict future driving conditions from current data [42,43]. In addition, several hybrid approaches, such as the methodology suggested by Shen et al.[44], combine statistical and machine learning techniques. This approach utilizes the Markov model for speed prediction and then uses a BPNN for error correction.

However, these methodologies encounter several challenges. First, they often struggle to maintain accurate predictions across diverse driving environments and unforeseen circumstances. Second, the requirement for real-time prediction greatly increases the computational demands and complexity of the models. Finally, a significant dependence on extensive historical driving data can cause considerable limitations in terms of time and costs for data collection and processing.

In this study, we introduce the Driving Profile Extractor (DPE), a sampling-based method designed to extract a driving feature for the Multi-Feature Prediction Model (MFPM). In this framework, the driving profile X_{ijk} represents the k-th driving feature within the j-th segment of the i-th driving profile. A driving profile is essentially a hierarchical arrangement of the driving features, reorganized according to criteria derived from a vehicle's historical driving data. These profiles can be segmented based on various criteria related to these driving features. For example, a driving profile may be divided into six segments, each described by different time slots of the day, such as midnight to 4 AM, 4 AM to 8 AM, and so on. In this setup, a vehicle's driving features, derived from historical driving data, are assigned to each time-based segment. Alternatively, a simpler profile might be comprised of just two segments, representing AM and PM periods, respectively. In such cases, X_{ijk} is normalized over the driving distance for scalability based on distance.

The DPE function $\mathrm{h}(\cdot)$ then extracts driving features from the driving profile X_{ijk}. As described in equation 7, DPE primarily uses driving distance D as the input variable. In this equation, P_{ij} represents the proportion of the j-th segment in the i-th driving profile.

$$\bar{X}^{*}_{ijk} = h\left(D \times P_{ij}, X_{ijk}\right), \text{ where } i = 1,2, \;\; j = 1,2,\cdots,s_i, \text{ and } k = 1,2,\cdots,t_j \qquad (7)$$

Furthermore, let $\bar{X}_{ij}$ be the average driving feature of the j-th segment of the i-th driving profile. The DPE utilizes the $\bar{X}_{ij}$ to combine the driving features of each segment proportionally, thus generating a driving feature representing the vehicle's overall driving characteristic, as in equation 8. It is allowing the generation of a driving feature from the single variable D, the driving distance, based on the vehicle's actual historical driving data.

$$X_i^* = \sum_{j=1}^{s_i} h(D \times P_{ij},\ \bar{X}_{ij}), \quad \text{where } i = 1,2. \tag{8}$$

D. Single Feature Prediction Model (SFPM) – Integration of DPE and MFPM

In this research, data from 37 Micro Electric Vehicles (MEVs) indicated an average driving distance of approximately 8 km. This indicates that they are commonly used for short-distance travel. However, a significant challenge arises when using the Multi-Feature Prediction Model (MFPM), which is typically trained on short-distance driving data, for the purpose of predicting long-distance trips. This can lead to increased prediction errors. To address this issue, we introduce the Single Feature Prediction Model (SFPM), which can accurately predict battery consumption for both short- and long-distance trips and only requires a single input variable.

The Single Feature Prediction Model (SFPM) uses the Driving Profile Extractor (DPE) to allocate driving distances. It then extracts driving features for each segment and predicts the battery consumption associated with these segments. The predictions for each segment are aggregated to calculate the overall battery consumption for the trip based on the driving distance D. For example, consider two distinct driving profiles as previously discussed: one segmented into six intervals of 6 hours each, and another divided into two intervals of 12 hours each. The SFPM is capable of generating two different sets of battery consumption predictions for D using these profiles.

Subsequently, these two prediction values are merged using a weight function that is optimized to minimize the prediction error. The following paragraphs provide more details on this evaluation method, including how the weight function was optimized.

The development of the Single Feature Prediction Model (SFPM) begins with employing the Driving Profile Extractor (DPE). For each driving profile i, the DPE is utilized to extract driving features for each segment (j) based on the driving distance D. It computes the average of these features, denoted as $\bar{X}_{ij}$, and transforms them into $\bar{X}_{ij}^{*}$ using the function $h(\cdot)$. Here, P_{ij} serves as the predictive variables for the Multi-Feature Prediction Model (MFPM).

To effectively aggregate the prediction results from each driving profile (i), optimization of the weight function D is necessary for combining the two values. Figure 4(a) illustrates this concept. In this figure, gray dots indicate the actual battery consumption values for various driving distances. The red solid line corresponds to predictions made using a driving profile with a single segment, whereas the blue solid line represents predictions using a driving profile segmented into six parts.

As illustrated in Figure 4(a), the prediction performance of the MFPM varies depending on the driving profile used, particularly over different driving distances. The results from the MFPM with a single-segment profile show better accuracy for shorter distances, but this accuracy diminishes over longer distances. Conversely, the performance of the six-segment profile slightly decreases in accuracy for short distances but demonstrates superior performance for longer distances. This observation suggests that employing various driving profiles and their strategic combinations can enhance overall prediction accuracy. Subsequently, we explored a method of combining DPE outputs that minimizes the Mean Absolute Percentage Error

(MAPE) between the actual and predicted values.

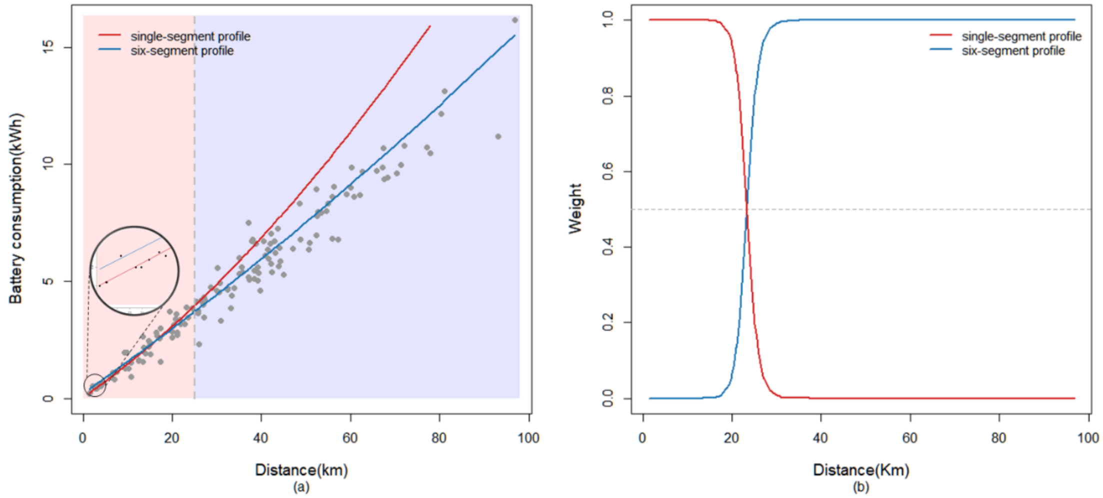

Figure 4 : Example of SFPM weight function

In the next stages, we establish a weight function using the sigmoid function to integrate the battery consumption prediction results from each driving profile. The process for determining this weight function includes several stages:

1. Prediction of Battery Consumption: Initially, the Multi-Feature Prediction Model (MFPM) is utilized to predict battery consumption over various driving distances for each profile.
2. Computation of Percent Error (PE): calculate the PE of these predictions, as defined in Equation 9.
3. Calculation of Differences in PEs: The difference in PEs between the two driving profiles is computed, denoted as $\Delta(D)$. To enhance the accuracy of these values, a smoothing spline technique is employed.
4. Interpretation of $\Delta(D)$: The $\Delta(D)$ values, assessed across different driving

distances, indicate the relative performance of each driving profile. For instance, if $\Delta(D)$ represents the difference in PE between MFPM predictions for single-segmented and six-segmented driving profiles, then at a specific driving distance D, a value of $\Delta(D) > 0$ suggests superior performance of the six-segmented profile, $\Delta(D) = 0$ implies equal performance, and $\Delta(D) < 0$ indicates a more accurate single-segmented profile.

5. Determination of Weight Function: Using these $\Delta(D)$ values, we determine a weight function based on the sigmoid function, which assigns a weight value between 0 and 1, as illustrated in Equation 10. Figure 4(b) illustrate the weights assigned to each driving profile, derived from the results shown in Figure 4(a).

Finally, by integrating the driving profiles with the MFPM f_m through this weight function, we formulate the Single Feature Prediction Model (SFPM) f_s, as detailed in Equation 11.

$$PE = \frac{|\, y_i - \widehat{y_i} \,|}{y_i} \times 100 \tag{9}$$

$$W(D) = \begin{cases} \dfrac{1}{1+e^{\Delta}} & if D \leq Max(T_D) \\ \dfrac{1}{1+e^{smooth(Max(T_D))}} & if D > Max(T_D) \end{cases} \tag{10}$$

$$Y = f_S(D) = \sum_{i=1}^{2} W_i(D) \sum_{j=1}^{s_i} f_m(\bar{X}^*_{ij}), \text{ where } \bar{X}^*_{ij} = h(D \times P_{ij}, \bar{X}_{ij}) \tag{11}$$

	MLR	SVR	XGBoost	DNN
RMSE (kWh)	0.4573	0.4472	0.459	**0.4309**
MAPE (%)	**25.4076**	25.6963	27.5802	25.858
PCC (%)	94.65	94.73	94.64	**95.11**

Table 7 : Summary of SFPM performance using four machine learning models (Optimal scores in bold face)

To evaluate the Single Feature Prediction Model (SFPM), we converted the driving and battery consumption data into daily measurements utilizing test data from the 37 Micro Electric Vehicles (MEVs). Note that for training the Multi-Feature Prediction Model (MFPM), this data was segmented according to the criteria established for a single trip. We then compared the prediction performance using Multiple Linear Regression (MLR), Support Vector Regression (SVR), XGBoost, and Deep Neural Networks (DNN) models. These comparisons were based on the performance evaluation metrics previously applied in the MFPM, and the comparison of performance is shown in Table 7. Upon analyzing the data, the DNN model demonstrated best performance, achieving a Root Mean Square Error (RMSE) of 0.4309 kWh and a Pearson Correlation Coefficient (PCC) of 95.11%. Conversely, the MLR model shows a lowest Mean Absolute Percentage Error (MAPE) of 27.4076%.

E. Inference of Battery Consumption

Although point estimates derived from the driving distance D are valuable, they inevitably contain prediction errors. Therefore, providing interval estimates alongside these point predictions can be highly informative. In the literature, various studies have proposed methods for interval estimation [45,46,47]. There are two primary types of intervals used in this context: confidence intervals (CI) and prediction intervals (PI). While CIs are focused on addressing uncertainties arising from variations in model parameters, PIs additionally encompass the errors inherent in predictions. As a result, we adopt the PI for interval estimation, applying the bootstrap method. This approach is chosen to account for uncertainties not only in the model parameters but also those originating from prediction errors.

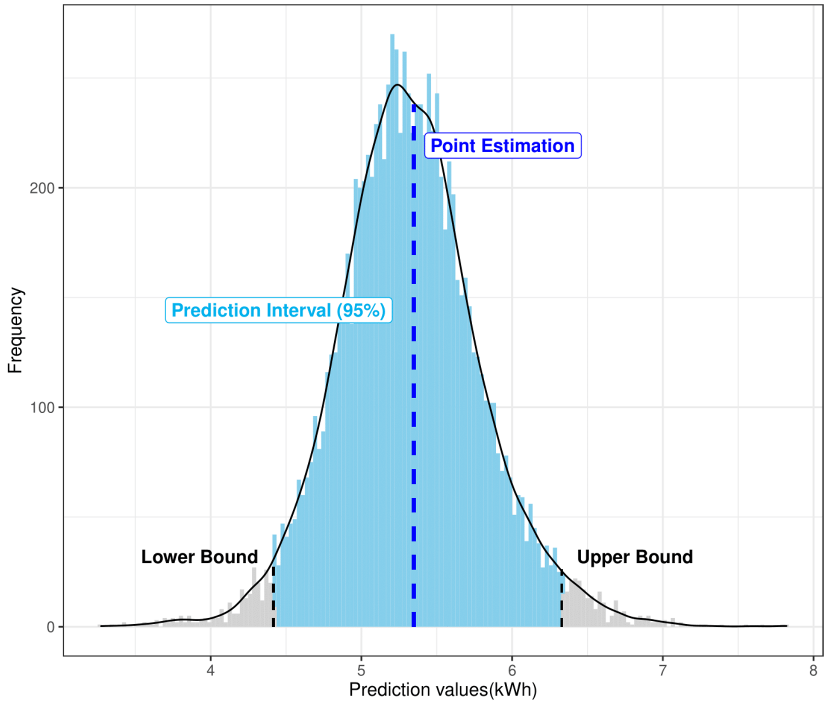

Figure 5 : SFPM point estimation and 95% prediction interval based on bootstrap

The bootstrap method, a widely recognized resampling technique, does not rely on the assumption of any specific probability distribution for variations. We detail the procedure for calculating the PI using bootstrapping in Algorithm 1. Figure 5 visually represents the computed point estimates and prediction interval of the Single Feature Prediction Model (SFPM). In this figure, the blue dashed line represents the point estimates, while the black dashed lines indicate the upper and lower bounds of the prediction interval.

Algorithm 1 Bootstrap-based prediction intervals algorithm
1: **Input**: Distance, Driving Profile Extractor (DPE), number of bootstrap samples B
2: **Output**: Bootstrap-based prediction intervals for battery consumption
3: Bootstrap sample set $\hat{Y}^* = \{\}$
4: for $b = 1, \dots, B$ do
5: Extract the b-th Bootstrap driving feature sample $X^*_{ij(b)}$ from at each i-th driving profile and j-th segment X^*_{ijk} based on DPE.
6: Extract the b-th Bootstrap residual sample res_b based on the residuals from the fitted MFPM.
7: Calculate $\hat{Y}^*_b = \sum_{i=1}^{2} W_i(D)(\sum_{j=1}^{s_i} f_m(X^*_{ij(b)}) + res_b)$
8: Append $\hat{Y}^*_b$ to the set $\hat{Y}^*$
9: Evaluate the Bootstrap-based prediction interval $PI^*_D = \left(\hat{Y}^*_{\left(\frac{\alpha}{2}\right)}, \hat{Y}^*_{\left(1-\frac{\alpha}{2}\right)}\right)$ from the bootstrap samples, where $\hat{Y}^*_{(c)}$ denotes the $(100 \times c)$-th percentile of $\hat{Y}^*$.

In order to evaluate the accuracy of the prediction model, we calculated three key metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Pearson Correlation Coefficient (PCC), as described in Table 7. In addition to these metrics, we considered two supplementary measures for evaluating the overall performance of the Single Feature Prediction Model (SFPM): The percentage of predicted values that fall outside of a 95% prediction interval and the average length of the prediction interval. The results of this performance comparison are presented in Table 8.

	MLR	SVR	XGBoost	DNN
Percentage of predicted values that fall outside of 95% PI	2.45	**4.25**	11.84	7.05
Average length of Prediction Intervals (kWh)	1.737	**1.478**	0.963	1.317

Table 8 : Summary of SFPM's prediction interval performance using four machine learning models (Optimal scores in bold face)

It is observed that only the Support Vector Regression (SVR) model is closely aligned to the 95% confidence level. This study also looked at the average lengths of the prediction intervals and found that the SVR model has a narrower average width of 1.478 kWh than the Multiple Linear Regression (MLR) model. Figure 6 illustrates the actual values, predicted values, and prediction intervals of Single Feature Prediction Models (SFPMs) for different machine learning models using data from a single MEV. Taking into account both the prediction accuracy and the length of the prediction intervals, the SVR model was chosen as the preferred choice for battery consumption prediction. Its consistent alignment with the confidence level and narrower prediction intervals make it the most suitable model in this study.

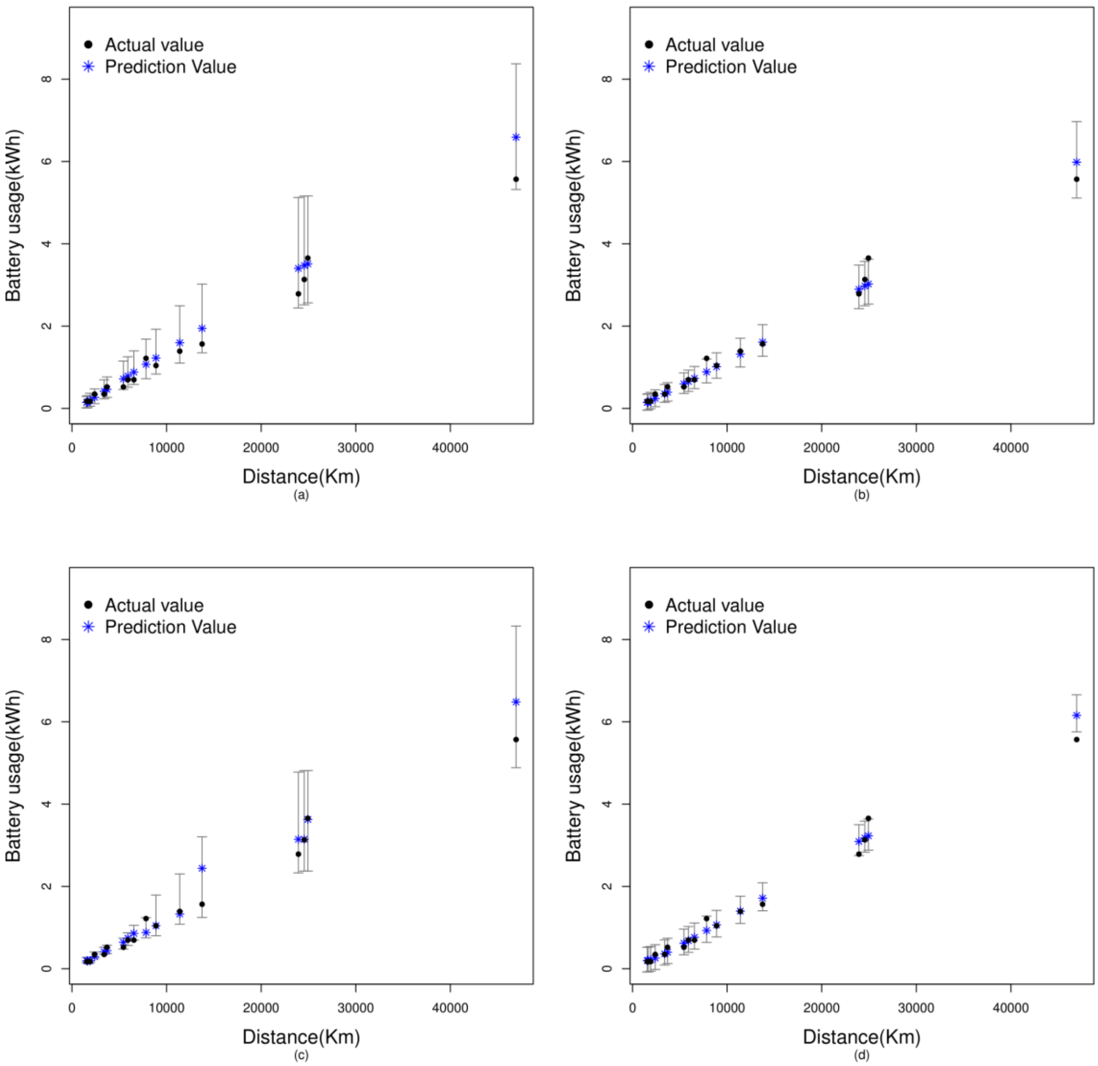

Figure 6 : Battery consumption prediction results obtained from SFPM for (a)MLR, (b)SVR, (c)XGBoost, and (d)DNN

The results that the SVR-based Single Feature Prediction Model (SFPM) predicted for a dataset randomly chosen from a single Micro Electric Vehicle (MEV) are shown in Figure 7. The figure includes histograms of the predicted values (blue dots), actual values (black dots), and prediction intervals (PIs). A close alignment of the predicted values with the actual values is observed, with the PIs centered around the point estimates. Furthermore, a clear pattern emerges: the PIs correspondingly widen as the driving distance rises. This pattern implies that over longer driving distances, the model takes into consideration more prediction uncertainty. In summary, the SVR-based SFPM not only delivers accurate predictions using driving distance as the single input but also provides prediction intervals that effectively account for this uncertainty. This approach ensures the accuracy of the data produced by the model, particularly in situations when there are variations in driving distances.

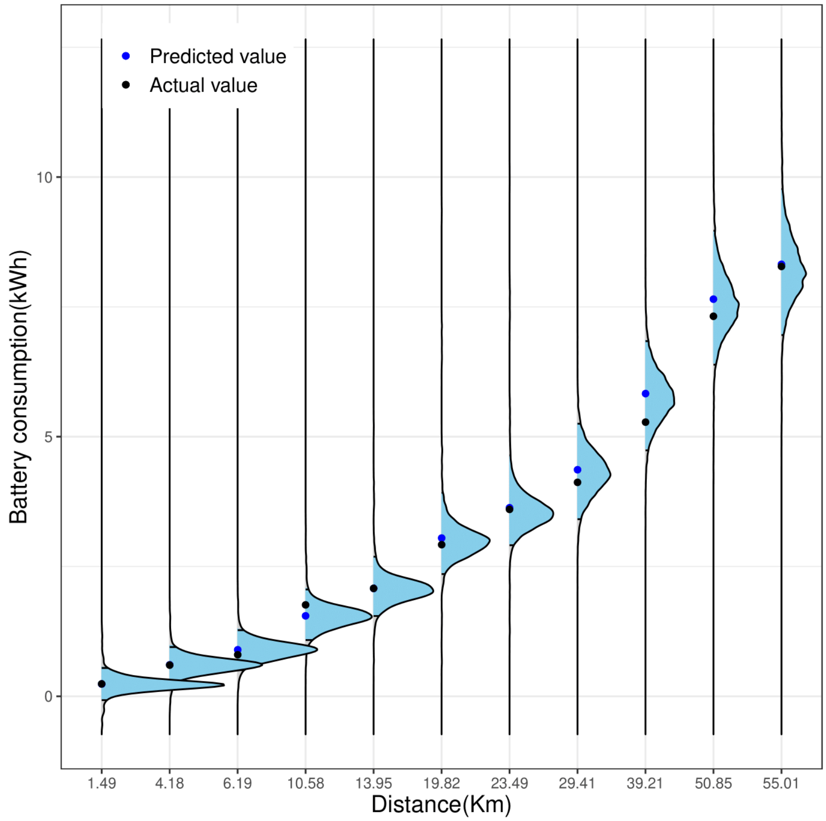

Figure 7 : SFPM prediction result based on SVR

IV. APPLICATION EXAMPLE – PREDICTION OF AVAILABILITY AND REMAINING DRIVING RANGE

A. Prediction of Available Driving Range

The Single Feature Prediction Model (SFPM) not only predicts battery consumption but also estimates available driving distances. Figure 8 illustrates the dual functionality of the SFPM, showing its capability to predict both battery consumption based on driving distance and the available driving distance given a remaining battery capacity. When a user provides a desired distance (D^*), the SFPM calculates a predicted battery consumption value ($f_S(D^*)$) along with its corresponding prediction interval $\left(\widehat{f_S(D^*)}+e\right)_{\left(\frac{\alpha}{2}\right)B}, \left(\widehat{f_S(D^*)}+e\right)_{\left(1-\frac{\alpha}{2}\right)B}$. Here, B denotes the number of bootstrap samples, and α represents the significance level used in the analysis. Conversely, for predicting the available driving range, the SFPM employs a method that is the opposite of the previous approach. By entering the current battery level of the vehicle, the inverse SFPM yields an estimate $(f_S^{-1}(y_c))$ and a corresponding prediction interval: $[Sup_D\left(\widehat{f_S(D^*)}+e\right)_{\left(\frac{\alpha}{2}\right)B} \leq y_c), Inf_D\left(\widehat{f_S(D^*)}+e\right)_{\left(1-\frac{\alpha}{2}\right)B} \geq y_c)]$. For instance, if a MEV has a remaining battery capacity of 6 kWh, the inverse SFPM with the bootstrap sampling method can estimate a driving range of 40.32 km, with a 95% prediction interval ranging from 34.08 km to 48.14 km. Consequently, the SFPM provides users with information regarding the required battery capacity to cover a specified driving distance and the available driving distance under the given battery capacity. This dual capability empowers users to assess their vehicle's battery status before starting a trip.

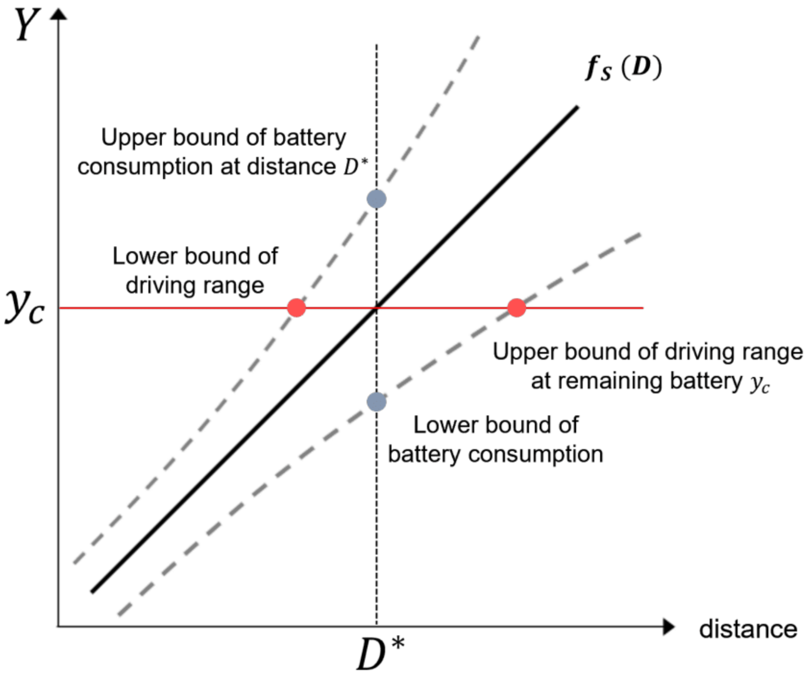

Figure 8 : Inference of Battery Consumption and Driving Range

B. Prediction of Vehicle Availability

Although the proposed SFPM enables users to estimate the battery consumption for a specific driving distance and the corresponding prediction interval (PI), some drivers still have concerns about potential battery shortages. So, we propose a method that calculates the driving availability for a specific distance based on the current remaining battery capacity. Availability indicates the probability of completing the driving distance based on the current battery capacity. Continuing on the example presented in subsection 4.1, let's consider a driving range of 45 km. The SFPM estimates the battery consumption for this distance to be 5.702 kWh, with a 95% prediction interval between 4.843 kWh and 6.659 kWh. Additionally, when assessing the availability with a remaining battery capacity of 6 kWh, the probability of successfully completing the trip is evaluated to be 72.73%. This probability is derived from the empirical distribution of the battery consumption for a specific driving distance (D^*) as determined by the SFPM. Figure 9 illustrates the idea of availability. The sky-blue section shows the probability of successfully completing a drive at different driving distances. Using this tool, users can assess the feasibility of driving a specific distance in advance.

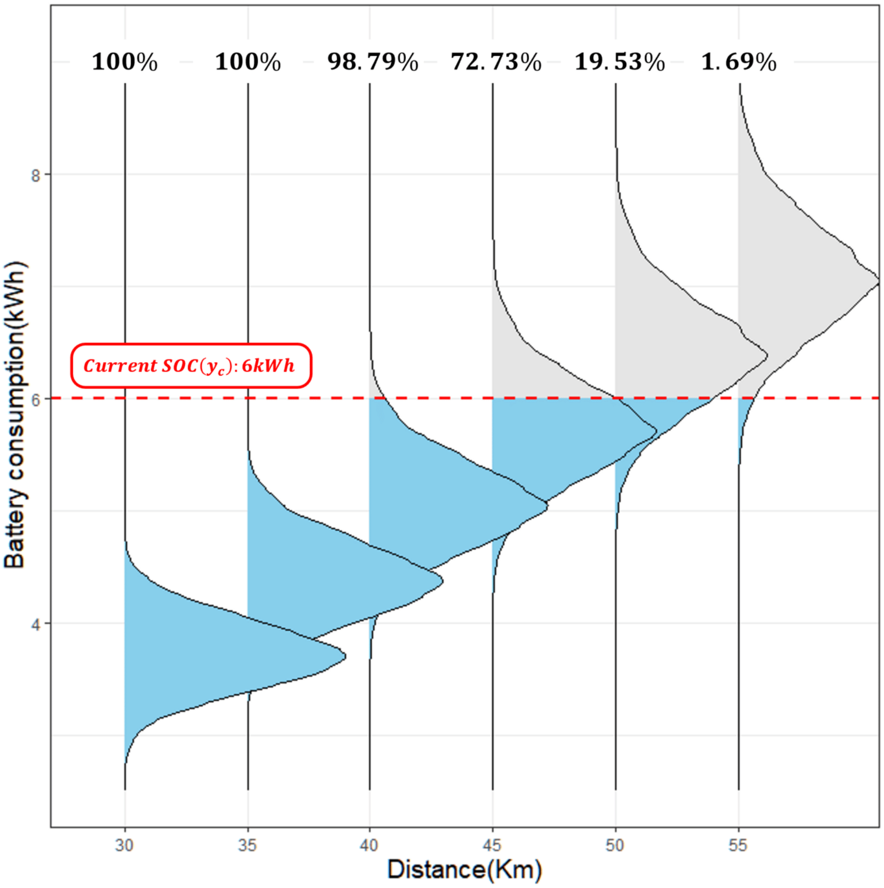

Figure 9 : Example of vehicle availability assessment

V. CONCLUSION

For drivers of Micro Electric Vehicles (MEVs), accurate prediction of battery consumption is still of the utmost concern. This research presents a new machine learning architecture that uses real driving data from 37 MEVs to estimate battery consumption. Additionally, it has practical uses such as predicting available driving distances and the probability of successfully completing trips based on the present level of battery capacity. The core of the suggested approach consists of three fundamental components. The Driving Profile Extractor (DPE) is used to extract characteristic information from historical vehicle data rather than make predictions about future driving conditions. Furthermore, to enhance the usability of the model, the driving distance is used as the main input variable for the DPE. Furthermore, the proposed approach evaluates the prediction interval by utilizing the bootstrap method. This allows users to obtain information, enabling them to make well-informed decisions when driving.

Throughout the model testing, especially for long-distance trips, the model showed significant effectiveness, achieving a root mean square error (RMSE) of 0.4472 kWh, a mean absolute percentage error (MAPE) of 25.6963%, and a Pearson correlation coefficient (PCC) of 94.73%. In addition, the model consistently maintained an outlier ratio of 4.25% with a 95% probability level and an average prediction interval width of 1.478 kWh. The usefulness of the suggested framework is further confirmed through various application examples.

Although the framework demonstrates promising predictive capabilities, there is still room for improvement. Subsequent investigations will concentrate on the expansion of the variety of predictive models that can be utilized within this framework as the process of collecting data continues for a longer period of time. In addition, we will focus on enhancing prediction accuracy by integrating elements such as battery performance degradation and various driving conditions.

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