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Electric Vehicles: Planning and Operations

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Contents

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Research Article

State-Flow Control Based Multistage Constant-Current Battery Charger for Electric Two-Wheeler

P. Balamurugan ,[1] Prakhar Agarwal,[1] Devashish Khajuria,[1] Devbrat Mahapatra,[1] S. Angalaeswari ,[2] L. Natrayan ,[3] and Wubishet Degife Mammo [4]

[1]*Electric Vehicle Incubation Testing and Research Centre, Vellore Institute of Technology, Chennai, Tamilnadu, India*
[2]*School of Electrical Engineering, Vellore Institute of Technology, Chennai, Tamilnadu 600127, India*
[3]*Department of Mechanical Engineering, Saveetha School of Engineering, SIMATS, Chennai 602105, Tamilnadu, India*
[4]*Mechanical Engineering Department, Wollo University, Kombolcha Institute of Technology, Kombolcha, South Wollo–208, Amhara, Ethiopia*

Correspondence should be addressed to P. Balamurugan; balamurugan.p@vit.ac.in, L. Natrayan; natrayanphd@yahoo.com, and Wubishet Degife Mammo; wubishetdegife7@gmail.com

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Battery charging is a greater challenge in the emerging electric vehicle domain. A newer multistage constant-current (MSCC) charging technique encompassing state-flow control tool-based design is implemented for charging the battery of an electric two-wheeler. MSCC method allows for faster charging and reduced battery degradation per charge. The designed controller incorporates line current power factor correction, thereby limiting the total harmonic distortion (THD) in line current and reactive power. The control strategy for battery charging has been developed using the state flow chart approach for implementing MSCC. The model has been formulated and implemented in MATLAB/Simulink. The proposed control monitors the state-of-charge (SOC) of the battery, age, and thermal behavior due to the charging strategy. The results show that the proposed charging technique with a state flow control approach gives effective and efficient output with reduced THD. Simulation results disclose that the desired parameters are controllable, stable, and effective within the operational limits.

1. Introduction

With growing pollution in urban India and climate change threatening the world, all countries and vehicle manufacturers are clear that the future of transportation is electric vehicles [1]. More than any other country, Indians ride 2-wheelers and India has around 7.35 million electric scooters and bikes, with the projected numbers for 2030 being around 26.52 million. And, the reason for the popularity of 2-wheelers in India is the price-sensitive market. The market for electric two-wheelers in India is growing rapidly, and the government is pushing for their adoption by giving incentives [2]. The market in India is very price-sensitive, and affordable scooters and affordable charging solutions will be paramount [3]. The conventional constant current-constant voltage (CC-CV) mode of charging and its drawbacks are increased time in CV mode [4]. The work aims to design an affordable charger with good charging speeds, exploring a newer method: the multistage constant current charging method. A fast-charging method considering the battery's safety/lifecycle and charging time is proposed in [5] by adopting the computation of internal dc resistance as a function of SOC and charging currents for a Li-ion battery. Considering the temperature rise of the Li-ion battery and charging time using an equivalent battery model, the particle swarm optimization technique is adopted to find the optimal charging technique [6]. The temperature rise can be improved by nearly 40% with an 18% reduction in charging time.

A Cuk-based resonant LLC converter was proposed for charging e-bikes considering the power quality of the input current in [7]. The pulse width modulation (PWM) based converter works in discontinuous mode. It has a single voltage loop simplifying its control with a maximum charging current of 10 A to charge a 20 AH battery following the IEC-61000-3-2 standard. An improved two-switch buck PFC incorporated SWISS rectifier-based charger for three-wheeler was proposed by [8], accommodating both fast and slow charging capabilities.

The problems associated with charging Li-ion batteries are mentioned as (i) increased temperature rise if the charging current is high with reduced charging time and (ii) increased charging time if the charging current is maintained within limits with good temperature rise. Various charging techniques for Li-ion batteries are adopted by considering the above-given limitations. Apart from the techniques, the charging pattern/algorithms are optimized and adopted for real-time implementation. Every method has its pros and cons; hence, there is always some compromise that must be made in charge. To reduce the charging time, current should be increased until the battery's temperature is within limits. Once the battery's voltage has reached the minimum level, the charging current is reduced to a lower value. At every stage, the SOC of the battery is monitored to fix the charging current reference for each stage.

In this manuscript, a novel state-flow approach-based controller design for multistage constant-current battery charging techniques was proposed and implemented for an electric two-wheeler. The strategy was formulated based on the survey conducted by the authors. This article briefs the literature on the selected problem statement in the introduction. The theoretical aspects of MSCC compared to the CC-CV algorithm were discussed in Section 2. The design approach adopted for developing the charger and the control algorithm was elaborated in Section 3. The design of the power converter and the development of the state-flow control algorithm were discussed, respectively, in Sections 4 and 5. The proposed concept was integrated and implemented in MATLAB/Simulink environment and obtained results. Electrical and thermal aspects of the battery and battery charger were inspected, and the results are presented in Section 6. Section 7 includes the conclusion that abstracts the simulation results with the possible future enhancement in the selected domain.

2. MSCC over CC-CV Charging Algorithm

Li-ion batteries and few types of batteries currently being utilized for electric vehicle applications [9] are charged using the traditional CC-CV technique and are preferred over other methods. Fast battery charging with better efficiency has continually emphasized charging techniques [10]. In CC-mode, a constant and higher magnitude current is used to charge the battery until it charges to its predefined threshold/cut-off voltage [11]. In CV-mode, a constant voltage of magnitude equal to the cut-off value of CC-mode is applied, resulting in a reduced charging current. Eventually, the current ceases when the battery potential is equal to the applied voltage [12]. Charging the battery at a large magnitude constant current followed by CV-mode prolongs the charging instance [13]. This eventually leads to adverse effects on the charging efficiency and capacity [14]. Hence, adopting the fast CC-CV charge method does not result in a feasible charging method that can be adopted for Li-ion batteries.

The multistage constant current technique is a new charging technique which charges the battery in the constant current mode in different stages with various stages of constant current to charge the battery fully. This method splits the battery charging time into multiple time instants. The battery is charged under constant current mode with different reference currents. The initial charging of the battery is considered at higher values. As the battery charges, the reference currents are reduced in the subsequent steps until the battery is full, as illustrated in Figure 1. The value of the reference current at each stage will be decided based on the battery capacity and SOC of the battery. Several optimization techniques can be employed to fix the reference current suitably. The charging methodology improves the battery life for many cycles with quick charging time and reduced losses. This method resolves the problem of lower current in CV mode in traditional chargers with a simultaneous reduction in charging time and cost of the charger.

The investigation of 13 charging patterns of Li-ion batteries is considered in [15] on the electrochemical effects of charging. EIS measurements were carried out after 300^{th}, 500^{th}, and 510^{th} cycles under 50% SOC. It is observed that the charging and discharging is affected by electrode reaction kinetics caused by diffusion of Li ions in the active material. Under MSCC, the cells attain smaller electrochemical polarization, and the maximum charging current is determined by the lithium plating boundary that determines the rapid charging ability of Li ion batteries. MSCC strategy results in high energy density pouch cells, with optimal charging combination under wide range of charging temperatures improving the cycle performance and shorter charging time.

3. Design Approach

3.1. Battery Capacity. Present 2-wheeler EV batteries do not exceed the power rating of 2.5 kW; hence, in the power converter design, all the components are selected to suit their operating power levels.

3.2. Use Case. The aim is to develop a charger that can be plugged in at home with single-phase supply for domestic use and is compact, low cost as possible without compromising the charging time and efficiency. Hence, a single DC-DC boost converter for PFC and charging algorithm applications is considered the best power converter choice.

3.3. Alternatives and Tradeoffs. Multistage constant current charging is not the current industry standard and is aimed at formulating an alternative to the conventional method of

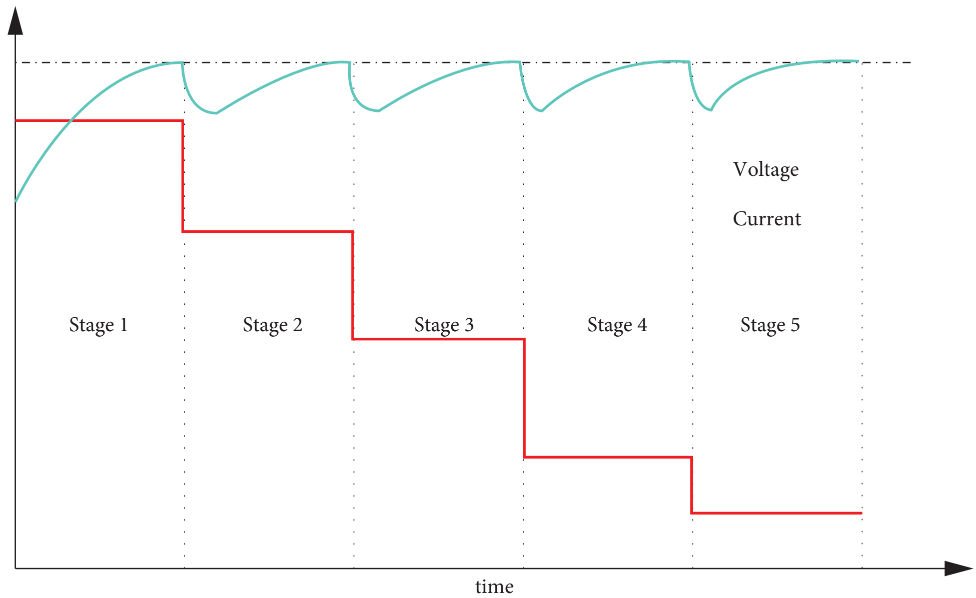

Figure 1: Illustration of MSCC technique for battery charging.

charging. The medium-long term impact of this method is under research.

3.4. Fundamental Battery Charging Circuit. The block diagram of the proposed multistage constant-current charger system is shown in Figure 2. From the domestic supply socket, a single-phase ac supply is connected to the step-down transformer to reduce the voltage compatible to charge the battery. Uncontrolled rectification of ac to dc is performed by a diode bridge rectifier. The output of the rectifier is fed to the PFC boost converter for appropriate conditioning of charging voltage and shaping the input AC. The PFC converters serve the dual purpose of regulating dc voltage and improving the AC input's power factor of the ac input. A suitable control strategy is vital in any charge controller, considering input ac voltage and battery side parameters for regulating the PFC boost converter [14]. The MSCC controller sets the battery's reference voltage and charging current, and the controller incorporates PFC. The controller receives information like source voltage, frequency, and phase from ac side and battery voltage, reference voltage, and SOC from the dc side using appropriate sensors. Here, it is proposed a charging algorithm that charges the battery at a constant current at different voltages as a function of SOC of the battery.

4. Design Specifications

The design parameters of the proposed battery charger for an electric 2-wheeler are provided in Table 1. The design involves designing of PFC boost converter, LC filter, and transformer with adjustable tap settings. The design of the PFC boost converter is discussed as follows.

4.1. Boost Converter with Additional LC-Filter. The circuit of the PFC-boost converter with an additional output LC filter is shown in Figure 3. The additional LC stage is provided to eliminate the switching frequency ripples at the boost converter's output. The design of the boost inductor and output capacitor is discussed.

Based on the duty ratio (D), the boost converter has its predefined limits of operation [16]. Within the limits of the duty ratio, the output voltage (V_b) of the boost-converter is given by: $V_b = V_{\text{in}}/(1-D)$. For an ideal boost-converter, a PWM duty cycle of $D=0$ leads to the output voltage equaling the input dc voltage (V_{in}), and for $D=1$ the output voltage tends to be infinite [17].

The value of boost inductance is calculated as

$$L_{in} = \frac{V_{in}D}{f_s \Delta I_L}. \tag{1}$$

The minimum output capacitance $C_{O(\min)}$ required is calculated based on input power (P_{in}) and peak inductor current (I_{pk}) as

$$\Delta I_L = 0.2 I_{pk}, \qquad I_{pk} = \frac{\sqrt{2}P_{\text{in}}}{V_{\text{in}(\min)}}, \tag{2}$$

$$C_{O(\min)} = \frac{I_{\text{OUT}(\max)}D}{f_s \Delta V_b}, \tag{3}$$

where ΔI_L is the inductor current ripple, I_{pk} is the peak current of the inductor, f_s is the switching frequency of the boost converter, and ΔV_b is the ripple in output voltage.

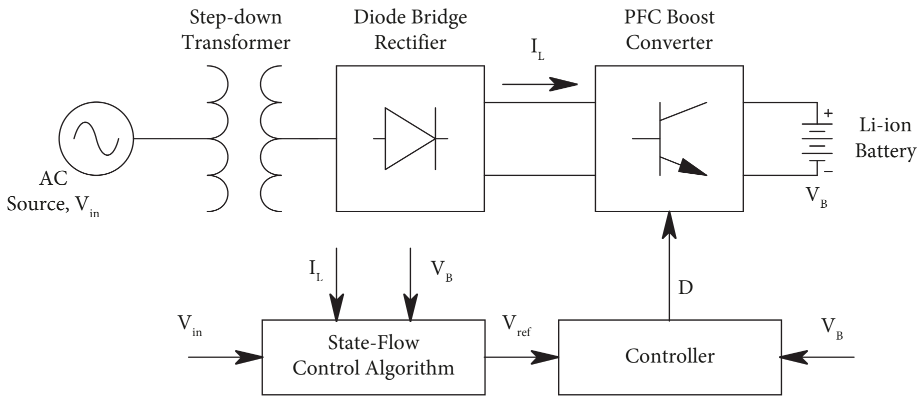

Figure 2: Block diagram of the proposed Li-ion battery charger with MSCC algorithm.

Table 1: System parameters.

Parameters	Values
Source voltage	1φ–230 V (RMS), 50 Hz
Variable ratio transformer	0.081
Boost inductor (L_{in})	2.1 mH
Output capacitor (C_{out})	150 μF
Switching frequency f_s	20 kHz
LC filter	
Inductor (L)	0.08 H
Capacitor (C)	90 mF
Battery specifications	
Nominal voltage	25.2 V
Rated capacity	49.4 Ah
Fully charged voltage	29.33 V

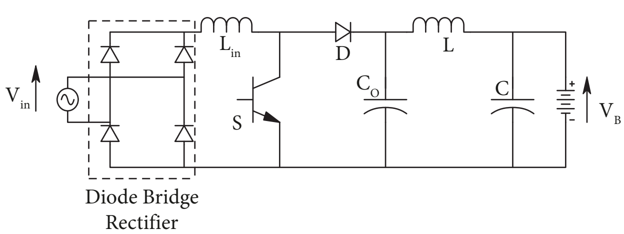

Figure 3: Basic charging circuit with PFC boost converter.

4.2. Controller. The controller is the major component of the control system that dynamically regulates charging current, charge voltage, and input power factor. The controller needs 3 measurements, namely,

(1) Measure the output voltage to keep it at the reference level (V_{ref})

(2) Measurement of the ac input voltage at the secondary side of the transformer to provide a reference for the inductor current, in such a way- the input AC in phase with input ac voltage

(3) Measurement of the average inductor current to ensure that it tracks the rectified AC voltage

The controller consists of two control loops as shown in Figure 4, a primary current-control loop and a secondary voltage-control loop. The voltage-control loop regulates battery voltage and the inner current loop shapes the dc-link current so that the input current tracks the input voltage both in shape and phase, ensuring a near unity power factor [18]. The working of the MSCC algorithm is described in Section 5.

4.2.1. Voltage-Control Loop. Voltage control loop regulates battery voltage by providing a current command to the inner current controller loop of the PFC controller [19]. This current is proportional to the magnitude of the charging current required to charge the battery. The battery voltage error is regulated by PI controller providing DC reference to the inner current loop [20].

4.2.2. Inner-Current Loop. In the inner-current loop, the reference current set by the voltage control loop is multiplied by the final shape of the supply voltage at unit magnitude. It is compared with the inductor current I_L of the boost converter [21]. The current error is fed to the PI controller, whose output is the desired duty ratio (δ). The signal is then fed to the pulse generator to trigger the power switch of the PFC boost converter [22].

5. State Flow Control Algorithm

Li-ion batteries are very sensitive to overcharge and variations in charge/discharge currents; therefore, a suitable charging algorithm is needed to maximize charging capacity, reduce charging time, and improve battery lifespan [23].

In the traditional CC-CV mode, a high magnitude constant current is supplied to the battery until its voltage reaches the peak value, after which that peak voltage is maintained and kept constant till the current decreases to its cut-off value and charging is stopped [24]. This consistent application of peak voltage can adversely affect the battery and increase charging time.

The multistage charging method is faster and more efficient than the conventional CC-CV method. It is implemented with 3-stage charging, where various stages have different current values. As charging starts, the highest current value is applied until the battery voltage reaches its peak value, upon which the current is reduced to its second

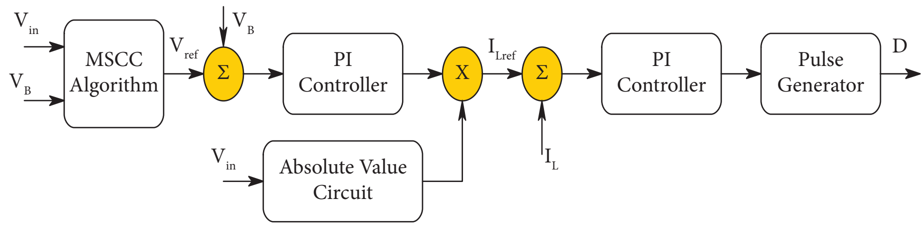

Figure 4: Block diagram of the charge controller.

stage value, which leads to a sudden drop in the voltage. This voltage then climbs to its peak value when the current is dropped again. This is the mechanism of multistage charging [25]. For the three stages, three charging current values are chosen. The first stage will have a constant value, the maximum allowed current (I_1) for the battery in CC mode. So, the charged AH capacity now only depends on the last stage current (I_3). The smaller the value of I_3, the higher the value of charged capacity. Now, as both I_1 and I_3 are selected, charging time depends only on I_2 and for different values of I_2, charging times will be different, but the AH capacity charged will approximately be the same as I_3 [26]. The optimum value of I_2 is selected by using the following formula:

$$I_2 = \sqrt{I_1 \times I_3}. \tag{4}$$

This control logic gives voltage reference to the controller, which then controls the current in the battery through boost PFC. The optimal value of I_2 is chosen based on Figure 5, which plotted the charging time as a function of charging current I_2. The total charging time T is minimum when the I3 has a value calculated by (3), and the optimal value is independent of the values of Req and Ceq instead depends on the values of I_1 and I_3. While computing I_2, the values of I_1 and I_3 are maintained constant. The lowest charging time corresponds to the value of $I_{2,}$ which satisfies that formula. The complete formulation of MSCC is shown in Figure 6 and is detailed in this section.

5.1. State Flow Chart Demonstration. In the first stage, the charger starts charging the battery at maximum current I_1, and achieving the current I_1 gives a voltage reference of 35 V. To avoid overlapping of all the stages simultaneously, an initial delay of 0.4 seconds is added due to a sudden increase in the voltage. To incorporate this, two blocks of the same stage are used with the delay between them.

In the second stage, where the current reference is I_2, the battery voltage rises to its peak value of 29.33 V, and the condition [$V_{peak} \leq V_b$] is met. The logic moves to the second stage with a reference voltage of 28.25 V. Again, to incorporate the slight delay in the reduction of voltage which might lead the control to cross all stages. Hence, a delay of 1 second is introduced and to do that, two blocks of the same stage are used.

After the battery voltage has climbed up to V_{peak}, the condition is met and moved to the third stage, where the process repeats. And finally, in the third stage, when the battery reaches its peak voltage, the charging is completed, and the reference voltage is now reduced to 0, inhibiting the current supply to the battery.

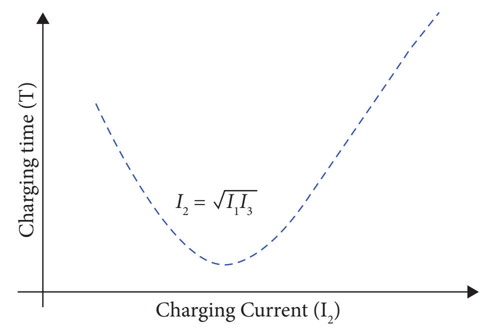

Figure 5: Relationship between charging time (T) and charging current (I_2).

6. Simulation Results

The proposed charging circuit is simulated with MATLAB Simulink. The block diagram is represented in Figure 7.

The output from the transformer is stepped down single-phase voltage. After stepping down the input voltage is passed through a full bridge rectifier which rectifies the AC into DC as shown in Figure 8. From the perspective of PFC, the load is connected to the battery's rectifier and a boost converter with capacitors and inductors. The load becomes more reactive because of these reactive components, which causes line current, i.e., current drawn from the AC supply to go out of phase with the line voltage, reducing the power factor. The shape of the line current becomes nonsinusoidal while line voltage stays sinusoidal. The nonsinusoidal line current increases reactive power and decreases active power. All these ill-effects caused by diode bridge rectifiers can be avoided by using the Boost PFC converter, and the results are shown in Figure 9, line voltage (V_{in}) is shown in blue while line current (I_{in}) is shown in red. Inductor current (I_L) is shown in red, while reference (I_{L_ref}) is shown in blue in Figure 10.

6.1. Power Factor Improvement. In the absence of a boost converter, the source current waveforms are observed at ac input spikes near the ac supply voltage peak. The waveform distortion evaluated using FFT analysis has a rich spectrum of harmonic frequencies that are odd integer multiples of the fundamental frequency. The THD of source current is 280%, with the corresponding power

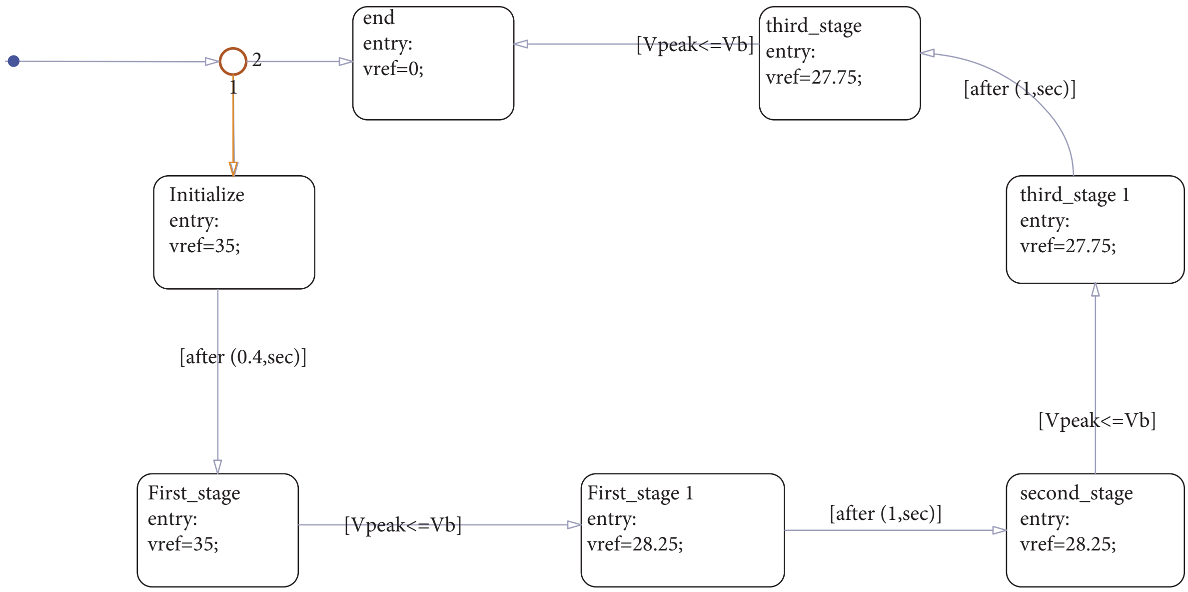

Figure 6: State flow control logic of the multistage current control algorithm.

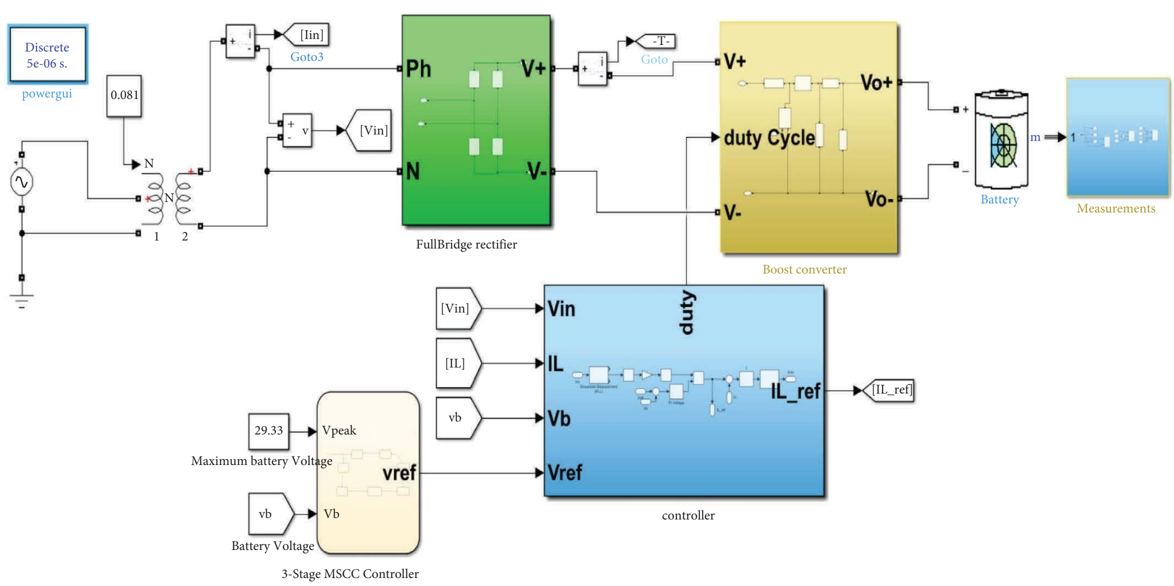

Figure 7: MATLAB simulink model.

factor of 0.33 lagging, which is very poor. The provision of a boost converter in the dc-link with a suitable control technique that shapes the source current to be in line with source voltage improves the source current waveform with reduced THD and improved power factor as discussed in this section.

FFT analysis of line current is performed in all three stages of charging to analyze the power factor improvement. The line current is directly proportional to the magnitude of the current supplied to the battery. The source spectrum is inversely related to the power factor, stating poor distortion in source current results in poor power factor. For all the FFT analyses a fundamental frequency of 50 Hz is set.

Figure 11 shows the FFT spectrum of ac line current in CCCV mode. A charging current of higher amplitude is chosen to limit the charging time of the battery on trivial basis. The line current THD is 15.82% which is far beyond the recommended limits specified by IEEE519: 2014 recommendations, and the power factor is computed to as Power factor $= \sqrt{1/1 + (15.82/100)^2} = 0.9877$ lagging.

Figure 12 shows the FFT analysis of line current in the 1st stage (stage of I_1 current). In this stage, the line current peak is 22.7 A, the corresponding THD is 9.26%, and the power factor is computed to as Power factor $= \sqrt{1/1 + (9.26/100)^2} = 0.9957$ lagging. The THD is significantly lesser than the CCCV adopted earlier.

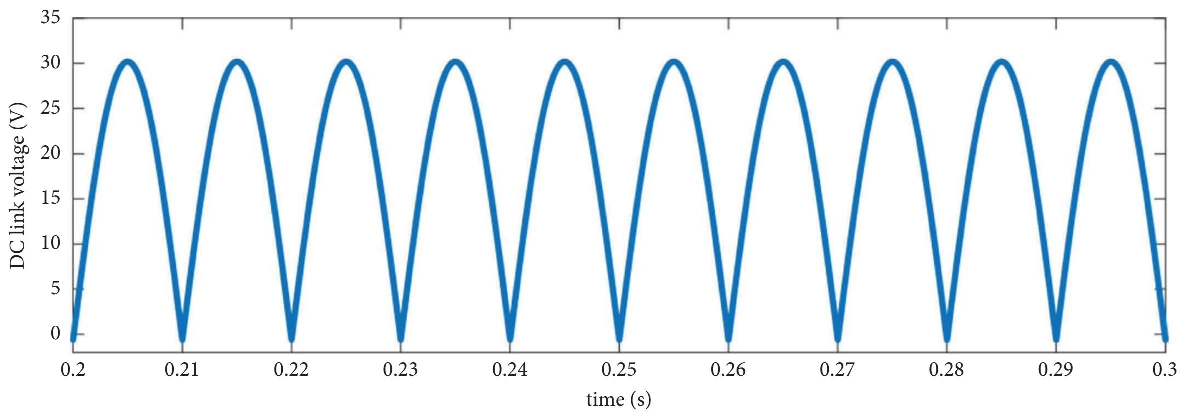

Figure 8: Output from full bridge rectifier.

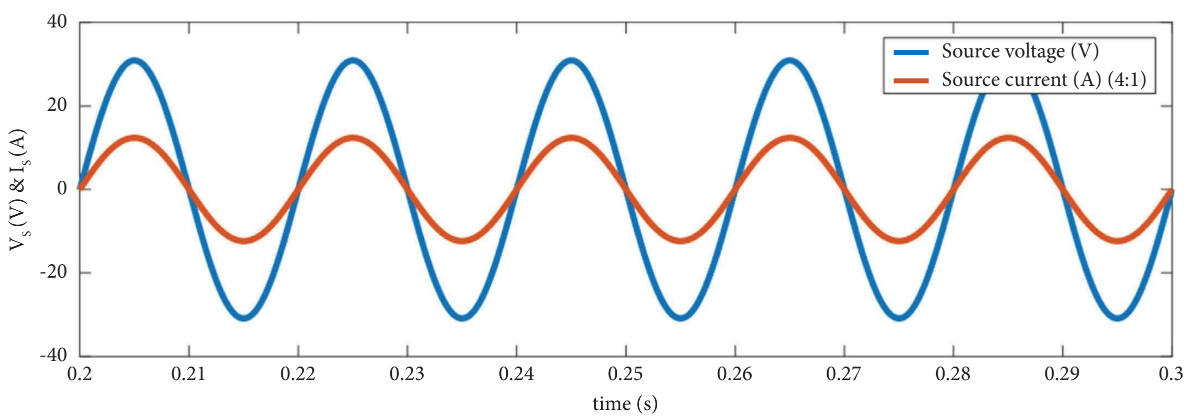

Figure 9: Line current in phase with line voltage after boost PFC.

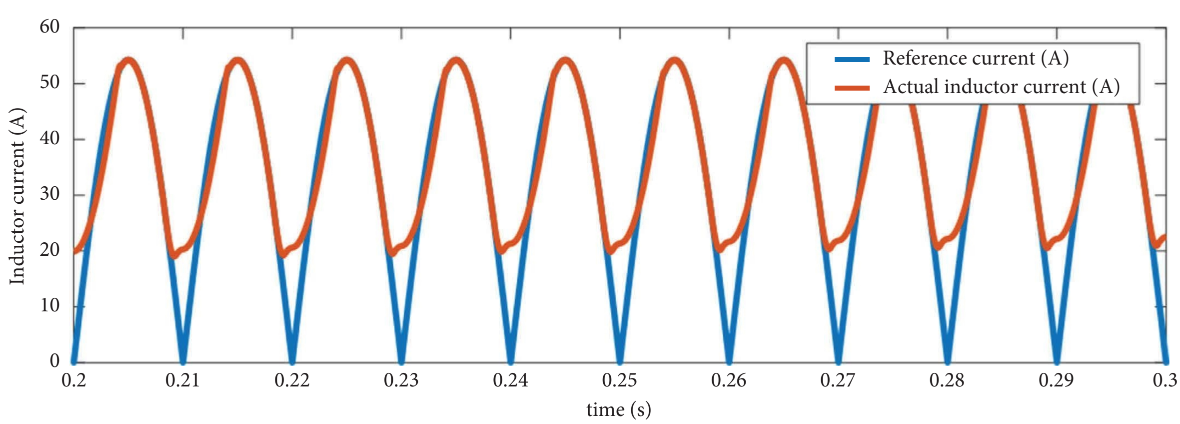

Figure 10: Inductor current in phase with reference current regulated by controller.

Figure 13 shows the FFT analysis of line current in the 2nd stage (stage of I_2 current). In this stage, the line current with a peak of 10.74 A with THD of 8.36%, and the power factor is computed to as Power factor $= \sqrt{1/1 + (8.36/100)^2} = 0.9965$ lagging, and the THD is significantly less.

Figure 14 shows the FFT analysis of line current in the 3rd stage (stage of I_3 current). In this stage, the line current with a peak of 7.92 A with THD of 4.5%, and the power factor is computed to as Power factor $= \sqrt{1/1 + (4.5/100)^2} = 0.9989$ lagging, and the THD is within IEEE519:2014 recommendation.

V_{peak} input in the state flow chart was reduced at various stages to demonstrate the charging stages as it consumes a longer run time. In stage 1, a current I_1 of 20 A is supplied to the battery, which leads to increase in voltage and SOC of the battery and V_{peak} is reduced to 27.83 V. The battery parameters and the charging profile are shown in Figure 15.

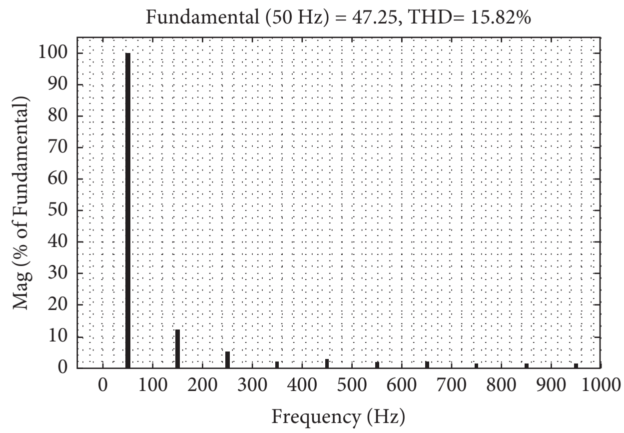

Figure 11: FFT spectrum of line current in CCCV.

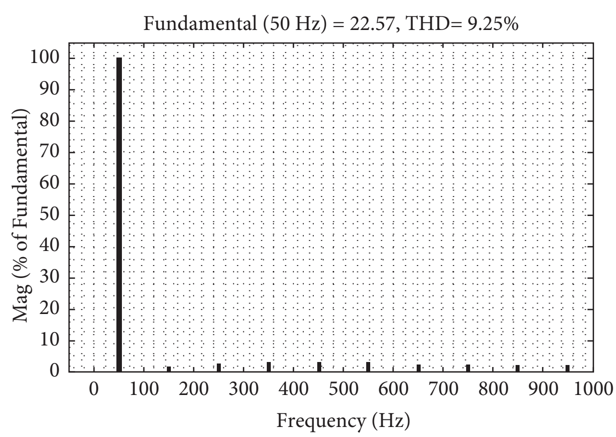

Figure 12: FFT analysis of the line current during first stage of MSCC.

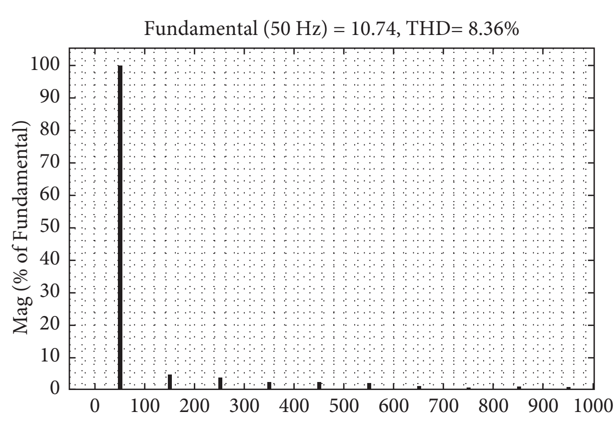

Figure 13: FFT spectrum of the line current during second stage of MSCC.

In stage 2, a current I_2 of 10.7 A is supplied to the battery, which leads increase in voltage and SOC% of the battery. When the battery voltage reaches 27.83 V the I_1 is reduced to $I_{2,}$ which leads to a decrease in voltage and decrease in the rate of charging of the battery because the charging rate depends on the magnitude of the supply current; this can be seen in the %SOC. When the battery voltage reaches 27.588 V, I_2 is reduced to $I_{3,}$ which again leads to a decrease

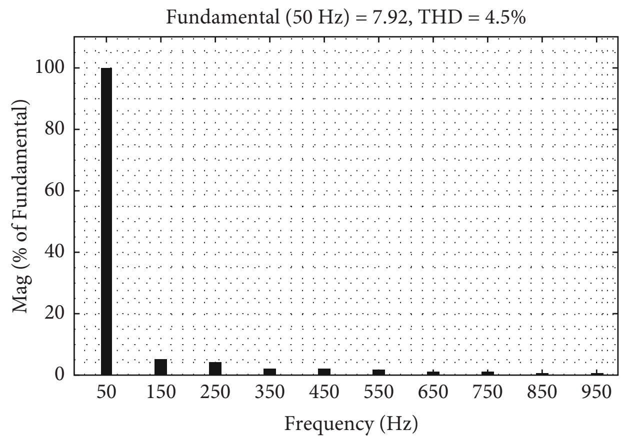

Figure 14: FFT spectrum of the line current during third stage of MSCC.

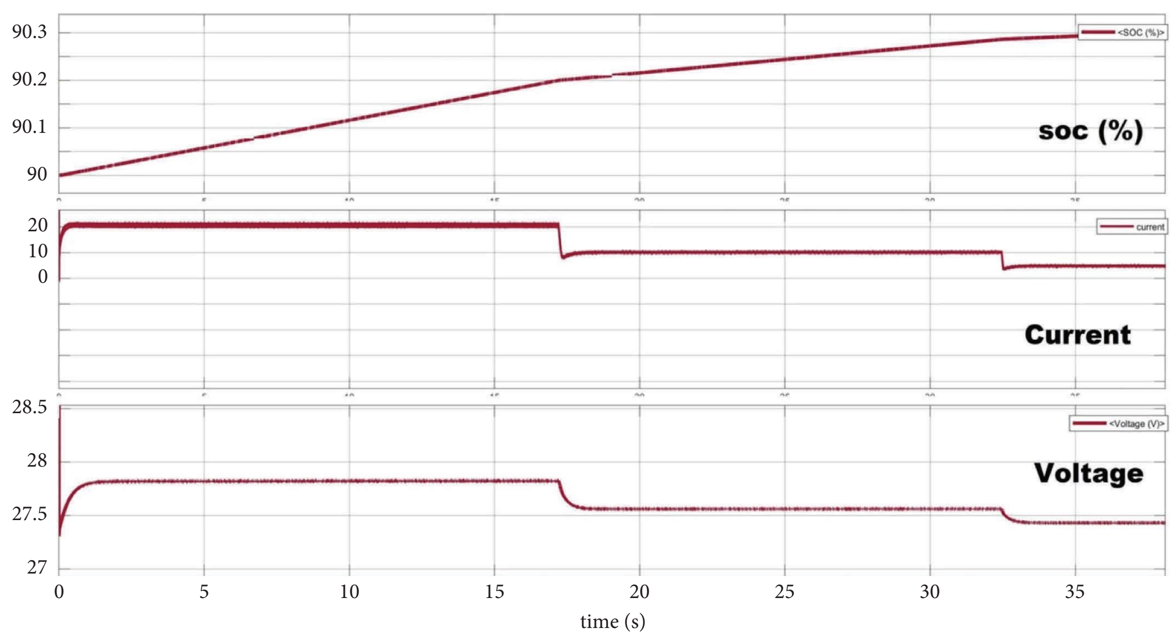

Figure 15: Status of battery: SOC, charging current and charging voltage.

in voltage and a decrease in the rate of charging of the battery.

Now in the 3rd stage, the charging current magnitude (I_3) of 5.7 A is set as reference and is charging the battery. The charging rate is even slower, following the protocol adopted by most battery chargers in today's world. In other words, at the lower SOC level, the battery needs to charge quickly with an elevated current level. The charging current should be relatively lower at a higher SOC level. The converter's efficiency with ideal components is calculated as the ratio of output power to the input power measured at the fundamental frequency, accounting for 93.78%. The nonideal behavior of the converter, effect of parasitic elements, and effect of noise signals are not considered for calculating efficiency. The ambient temperature of the battery is set initially at 25°C and later increased to 35°C, considering the ambient temperature of India. The performance of the charger is invariant. In practice, there will be a detrimental effect due to temperature variations due to environmental conditions. Hence, measures must be taken to isolate the battery packs exposed to direct sunlight and effective heatproofing. This will improve the battery life and enhance the safety of e-bikes by avoiding the attainment of higher temperatures of battery packs.

7. Conclusion

The multistage constant current technique for charging Li-ion batteries for two-wheeler electric vehicles was formulated and developed using a state-flow approach using MATLAB/Simulink. The performance of the MSCC-based charger was designed considering battery life, temperature rise, and line input current shaping with power factor correction. The concept of fast charging was implemented by considering SOC and battery voltage. The charging currents for the various stages were fixed considering the charging time of the battery, and the results are demonstrated. The input current spectrum of the charger indicates THD of the input currents is within limits at near unity power factor. The control strategy addresses the primitive design of battery chargers for e-bike applications which can be modified for three-wheelers. The research can further be extended by evaluating the battery capacity after charging and thermal analysis and considering the effect of small signal noise on the performance of the battery charger.

Data Availability

The data used to support the findings of this study are included in the article. Should further data or information be required, these are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Multiparadigm Modeling Framework to Evaluate the Impacts of Travel Patterns on Electric Vehicle Battery Lifespan

Shubham Agrawal ,[1] Srinivas Peeta,[2,3] and Mohammad Miralinaghi[4]

[1]*Department of Psychology, Clemson University, Clemson, SC 29630, USA*
[2]*School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA*
[3]*H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, GA 20332, USA*
[4]*Department of Civil, Architectural and Environmental Engineering, Illinois Institute of Technology, Chicago, IL 60616, USA*

Correspondence should be addressed to Shubham Agrawal; agrawa3@clemson.edu

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The widespread adoption of electric vehicles (EVs) can help attain economic and environmental sustainability by reducing oil dependency and greenhouse gas emissions. However, several issues need to be addressed before EVs can become a popular vehicle choice among the general public. A key issue is the perpetual reduction in EV battery capacity caused by battery degradation over time with usage. This can lead to a reduced driving range and cause "range anxiety" for EV drivers. This becomes even more critical in developing countries where consumers are highly sensitive to battery replacement costs. Thus, to promote EVs in developing economies, policymakers and vehicle manufacturers need to develop attractive incentive schemes and warranty strategies preceded by a thorough assessment of the useable EV battery lifespan for a wide range of users. This paper develops a multiparadigm modeling framework to compute battery degradation for a large population of EVs by capturing the effects of travel patterns, traffic conditions, and ambient temperature. The proposed framework consists of four different building blocks: (i) a microscopic traffic simulation model to generate speed profiles, (ii) an EV power consumption model, (iii) a battery equivalent circuit model, and (iv) a semiempirical battery degradation model. The proposed framework can also be used to assess the battery life-cycle of electric-powered automated vehicles by adjusting their travel patterns accordingly. A case study is presented using travel diary data of around 700 households from the U.S. National Household Travel Survey of 2009 to simulate household travel patterns and corresponding battery lifespan distribution.

1. Introduction

The transportation sector's share of energy consumption has been steadily increasing in developing economies like India [1]. This makes the transportation sector in developing countries one of the major contributors to urban air pollution [2]. Electric vehicles (EVs) have zero tailpipe emissions, making them a promising alternative to conventional fossil fuel-based vehicles for curbing greenhouse gas emissions [3]. EVs can also potentially reduce national oil dependency as the renewable and nuclear energy sectors grow. Several automobile companies have already introduced EVs to the market. For example, in 2021, Volvo announced a plan to cease ICEV production from 2030 onwards and to produce only BEVs and PHEVs [4]. Policymakers are also currently offering incentives to encourage the purchase of EVs [5]. For example, under the clean vehicle rebate project [6], the California Environmental Protection Agency (CalEPA) provides a rebate of up to $7,000 for EV purchases.

Despite international efforts, the greater adoption of EVs still faces several challenges. For example, the reduced maximum driving range due to battery degradation can accentuate range anxiety (i.e., the fear of running out of battery charge before completing the trip) among EV drivers over time [7, 8]. The costs associated with battery replacement from degradation can further deter EV purchases. This impending inconvenience and economic burden make affordable EVs unattractive for new automobile buyers, especially in developing countries where consumers are more sensitive towards costs. The scarcity of information on battery degradation and contributing factors also plays a critical role in increasing consumer skepticism. A thorough understanding of the effects of travel patterns, driving characteristics, and environmental factors on EV battery lifespan would assist vehicle manufacturers and policymakers in designing appealing incentive schemes and warranty strategies to increase EV adoption [9]. It can also help consumers make informed decisions based on their travel patterns and driving behaviors.

In this context, this study proposes a multiparadigm modeling framework to estimate the useable battery lifespan of a large population of EVs. The useable battery lifespan is defined as the duration within which the maximum EV battery capacity degrades below a certain threshold of its original capacity and needs to be replaced for regular use. It is an important factor in deriving the energy consumption estimation model for EVs [10]. The generally accepted battery degradation threshold before it needs replacement is considered to be 20 to 30% of its original capacity [11, 12]. The proposed modeling framework consists of four different building blocks: (i) a network-level microscopic traffic simulation model to obtain realistic drive cycles or speed profiles (i.e., a series of vehicle speeds versus time) of the vehicles; (ii) an EV power consumption model to compute the power profile from the speed profile; (iii) a battery circuit model that converts the power profile to a battery current flow profile; and (iv) a semiempirical battery degradation model that simulates battery lifespan based on current flows and ambient temperature. The multiparadigm approach provides the flexibility to use the most suitable modeling methods at each step. Some studies have used multiparadigm or multistage approaches in EV-related research, including digital battery lifespan management [13]; however, to the best of our knowledge, they have not been used to understand the impacts of travel patterns on the battery lifespan.

Battery degradation or battery aging can be classified into two different mechanisms: calendar aging (during storage) and cycle aging (during use). Aging happens as a result of structural disordering, variation in electrolyte composition, or loss of active material caused by thermodynamic instability [14, 15]. Calendar aging is mainly caused by the growth of a protective layer at the anode called solid electrolyte interphase (SEI), which results in the loss of active material (e.g., lithium) and increased electrode impedance [14, 16]. Cycle aging is mainly caused by structural changes and chemical decomposition of active material at the cathode and changes in SEI at the anode from electrolyte reactions during charging and discharging [17]. Although total degradation is considered as the summation of both calendar aging and cycle aging, their degradation mechanisms are not independent, and interactions occur [17]. This study focuses on modeling Li-ion battery degradation since most commercially available EVs use lithium-ion (Li-ion) battery packs [8]. Due to the inherent complexity of aging mechanisms and their interactions, several semiempirical battery degradation models [11, 18–21] and statistical models [22] based on experimental data have been proposed in the past literature.

Several efforts have been made in the past to quantify the useable battery lifespan of EVs. For example, Marano et al. [23] and Onori et al. [24] proposed a model to compute battery degradation for plug-in hybrid electric vehicles (PHEVs) using depth-of-discharge (DoD) (i.e., the percentage of battery capacity used before recharging) and battery temperature using linear combinations of standard driving schedules like the Urban Dynamometer Driving Schedule (UDDS) [25], which limits its applicability to a large population of EVs with diverse travel patterns and driving behavior. Guenther et al. [26] investigated vehicle-to-grid applications for synthetic drive cycles using a simplistic energy-based battery model, which ignores the effects of internal resistance and cell voltage at different state-of-charge (SOC) (i.e., the percentage of battery capacity available). Peterson et al. [27] analyzed vehicle-to-grid applications using UDDS and concluded that using a realistic drive cycle is important to quantify battery degradation as DoD may provide misleading results. Some studies have evaluated the impacts of battery recharging strategies on battery degradation using a combination of DoD, SOC, and/or temperature [28, 29]. However, these models assume a very simplistic drive cycle with little or no variation in speed and, hence, the current flow through the battery. Remmlinger et al. [30] presented a method to compute the degradation index relative to the degradation of new batteries by using the measurement values of cell voltage and current flow. Pelletier et al. [31] provide a brief overview of several Li-ion battery degradation models that can be used for EV applications. The proposed multiparadigm framework extends the existing battery lifespan computation frameworks by introducing a microscopic simulation layer to assess heterogeneity in travel patterns and driving behavior. Yang et al. [32] developed a novel analytical framework to determine battery degradation based on travel demand and the ambient high temperature of the battery. Their results show that battery life ranges from approximately 5 years in Florida to 13 years in Alaska, the United States. They also showed that if an EV continues to operate after the 30% battery degradation limit, the greenhouse gas emissions and energy consumption can be significantly increased. Xu et al. [33] proposed a Q-learning-based strategy to minimize Li-ion battery degradation and energy consumption. The Q-learning method is an adaptive optimal control algorithm that uses the Bellman equation of dynamic programming. It is shown that Q-learning decreases the battery capacity loss and increases the lifespan by 13-20%. A summary of the literature on battery degradation models is presented in Table 1.

The key contributions of this research are threefold. First, this study proposes a multiparadigm modeling methodology to derive the useable lifespan of battery of a large population of EVs. Second, this study integrates a microscopic traffic simulation model to account for the driving behavior heterogeneity for battery lifespan

Table 1: Summary of the literature on battery degradation models.

Study	Degradation model	Cycle life	Calendar life	Input
Marano et al. [23]	Damage accumulation model	Y	N	Current severity relative to battery size (i.e., C-rate), temperature, DoD, and SOC
Peterson et al. [27]	Integrated driving and energy use profile modeling framework	Y	N	C-rate, discharge power rate, DoD, and driving profile
Remmlinger et al. [30]	Internal resistance dependent degradation model	Y	N	Temperature, SOC, and power demand
Onori et al. [24]	Weighted Ah-throughput model	Y	N	Temperature and DoD
Guenther et al. [26]	Energy-based battery model	Y	Y	Temperature and power demand
Ouyang et al. [34]	Prognostic and mechanistic model	Y	N	C-rate and temperature
Yang et al. [32]	Pseudo two-dimensional battery capacity fading model	Y	Y	Temperature, travel demand, and driving profile
Calearo et al. [35]	Integrated thermal and SOC dynamics model	Y	Y	Temperature and SOC
Motapon et al. [36]	Physical degradation model	Y	N	C-rate, temperature, and DoD
Olmos et al. [37]	Empirical degradation model	N	Y	C-rate, temperature, DoD, and SOC
Xu et al. [33]	Control-oriented cycle-life model	Y	Y	C-rate, temperature, and SOC
Our study	Semiempirical traffic simulation-based degradation model	Y	Y	C-rate, temperature, travel demand, and driving profile

estimation. Third, each component of the multiparadigm method offers the flexibility to incorporate even newer models or real-world data without changing the framework's overall structure. For instance, real-world vehicle speed data, if available, can replace the traffic simulation model.

The following section introduces the multiparadigm modeling framework to quantify battery lifespan for a large population of EVs and discusses each building block in detail. Then, a case study for the city of Indianapolis, U.S., is presented, and the results are discussed to illustrate the impacts of travel patterns, driving behavior, and temperature on battery lifespan. The paper concludes with a discussion on potential applications of the proposed framework and insights for policymakers, vehicle manufacturers, and other stakeholders to aid greater EV adoption.

2. Methodology: Multiparadigm Modeling Framework

The proposed framework is composed of four modeling stages. This framework requires household vehicle travel patterns as input, which can be obtained using resources such as the U.S. National Household Travel Survey [38]. At a minimum, household vehicle travel patterns should include details about departure time, travel time, and distance traveled for all trips made by a particular vehicle on a given day. The microscopic traffic simulation model based on a real-world road network is calibrated using available traffic demand data to generate realistic drive cycles. Each trip in household travel patterns is then matched to a suitable drive cycle generated by the traffic simulation model. The speed profiles are then fed into an EV power consumption model to compute the power profiles. A battery equivalent circuit model is then employed to get a time series of current flow and SOC of the EV battery. These data are subsequently inputted to a semiempirical battery degradation model to calculate the battery state-of-health (SOH) (i.e., the ratio of current battery capacity to its original capacity).

2.1. Microscopic Simulation Model. Traffic simulation models are widely used to capture nonlinear interactions between vehicles and infrastructure at a microscopic level. Such models can simulate vehicle dynamics and output dynamic variables like position, speed, and acceleration for a large number of vehicles. In this framework, a time series of vehicle speeds is needed to compute the power requirement from the EV battery for propulsion. The simulation model needs to be calibrated using travel demand data between origin-destination pairs for the given road network. The aforementioned information can be gathered from multiple sources, like regional traffic management websites and open-source online resources (e.g., OpenStreetMap). The realism of the simulation model can be further enhanced by including more information such as traffic management infrastructure (e.g., traffic signals) and driver behavior (e.g., car-following model parameters). The simulated drive cycles are then used as input for the EV power consumption model discussed below.

2.2. Electric Vehicle Power Consumption Model. EV power consumption depends directly on the vehicle speed profile. Since the kinetic energy of a vehicle depends on its speed, it is necessary to capture changes in the speed at a microscopic level to accurately compute the vehicle's power requirements. Some simulation packages such as ADVISOR [39] and Autonomie [40] can compute energy consumption and MPGe (miles per gasoline equivalent) using drive cycle data. These tools simulate a detailed EV drivetrain system and hence are computationally expensive. Since a key application of the proposed framework is to quantify battery degradation for a large population of EVs, it is important to select a computationally efficient model at each step. This study adopts a physical model proposed by Van Haaren [41] to compute power consumption. This approach is used for the following reasons: (i) the model parameters are fitted using real-world Tesla Roadster data [42], and (ii) the computational runtime is significantly lower than the simulation packages mentioned before. This framework provides flexibility to use other similar EV power consumption models that take speed data as a primary input [43, 44].

The physical model used in this study computes the net vehicle power loss/gain (P_{net}) as the sum of two components. First, the power required to maintain a constant speed (P_{cons}). Second, vehicle power requirements at variable speed during loss/gain in kinetic energy while accelerating or braking (P_{kin}). The power loss/gain due to road grade is assumed to be zero but can be added to this model by considering the power gain/loss due to the change in potential energy of the vehicle (P_{pot}). The total power loss (in Watts) at constant speed is the sum of power losses due to aerodynamics (P_{ar}), drivetrain (P_{dr}), rolling friction (P_{rr}), and ancillary systems (P_{an}) as expressed in equations (1)-(6). The parameter definitions and values are presented in Table 2. Some of the parameter values are adapted to match the [43] model, a plug-in electric compact car that accounted for more than 23% of plug-in EV sales in the U.S. in 2013 [45].

$$P_{ar} = \frac{1}{2}\rho A_{veh} C_d V^3, \tag{1}$$

$$P_{dr} = \alpha_{dr} V_{mph}^3 + \beta_{dr} V_{mph}^2 + \gamma_{dr} V_{mph} + c_{dr}, \tag{2}$$

$$P_{rr} = c_{rr} \mathrm{mg} V, \tag{3}$$

$$P_{anc} = 180, \tag{4}$$

$$P_{pot} = \mathrm{mg}(V \sin\theta), \tag{5}$$

$$P_{cons} = P_{ar} + P_{dr} + P_{rr} + P_{an} + P_{pot}. \tag{6}$$

The total kinetic energy (in Joules) of the vehicle (E_{kin}) consists of linear kinetic energy (E_{lin}) and rotational kinetic energy (E_{rot}). For simplicity, the model assumes that the rotational kinetic energy is approximately 5% of the linear kinetic energy. The power loss/gain at variable speed is the change in kinetic energy (ΔE_{kin}) for the given time interval (Δt) as expressed in equations (7)-(9).

$$E_{lin} = \frac{1}{2} m V^2, \tag{7}$$

$$E_{kin} = E_{lin} + E_{rot} \cong 1.05\, E_{lin}, \tag{8}$$

$$P_{kin} = \frac{\Delta E_{kin}}{\Delta t}. \tag{9}$$

The net power loss is multiplied by the battery-to-motor efficiency factor to account for the inefficiencies in electrical to kinetic energy conversion. Similarly, the regeneration efficiency factor is multiplied to account for the energy recuperation from the regenerative braking system in case of net power gain. The net power consumption of EVs is bounded by their battery limits as expressed in equation (10). This framework assumes these limits as −7 kW (P_{min}) and 100 kW (P_{max}).

$$P_{net} = \begin{cases} P_{max}, & \dfrac{(P_{cons} + P_{kin})}{\beta_{eff}} \geq P_{max}, \\ \dfrac{(P_{cons} + P_{kin})}{\beta_{eff}}, & (P_{cons} + P_{kin}) \geq 0, \\ \beta_{rbs}\,(P_{cons} + P_{kin}), & (P_{cons} + P_{kin}) < 0, \\ P_{min}, & \beta_{rbs}\,(P_{cons} + P_{kin}) \leq P_{min}. \end{cases} \tag{10}$$

2.3. Battery Equivalent Circuit Model. Cycle aging primarily depends on the current flow through the battery during charging or discharging (or C-rate). A 1 C rate is defined as the theoretical discharging current drawn from the battery that will discharge the entire battery in an hour at its rated nominal voltage. A 2 C rate implies double the amount of discharging current corresponding to the 1 C rate; that is, it will discharge the battery in half an hour. This framework implements a battery equivalent circuit as illustrated in equations (11)-(16). The parameter values for Reference [46] are obtained from its owner's manual [46] and advanced vehicle testing activity data [47]. Model parameter definitions and values are presented in Table 3. The model uses 1-D lookup tables to get the cell internal resistance $\mathbf{R}_{int}(\mathbf{t})$ during charging/discharging and open-circuit voltage $\mathbf{V}_{OC}(\mathbf{t})$ at different SOC, as illustrated in Figures 1 and 2, respectively. Due to the lack of data, the internal resistance and open-circuit values are assumed to be constant until the battery's end-of-life (EOL). This assumption can be relaxed by using 2-D lookup tables containing internal resistance and open-circuit voltage values with respect to both battery SOC and SOH, if such data are available.

$$V_{cell}(t) = V_{OC}(t) - R_{int}(t) \cdot I_{cell}(t-1), \tag{11}$$

$$P_{chg}^{max}(t) = \frac{-V_{out}^{max}\left(V_{out}^{max} - V_{OC}(t) \cdot N_s\right)}{R_{int}(t)} \cdot N_t, \tag{12}$$

$$P_{dis}^{max}(t) = \frac{V_{out}^{min}\left(V_{OC}(t) \cdot N_s - V_{out}^{min}\right)}{R_{int}(t)} \cdot N_t, \tag{13}$$

$$\widetilde{P}_{out}(t) = \begin{cases} P_{dis}^{max}(t) & P_{out}(t) \geq P_{dis}^{max}(t) \\ P_{out}(t) & P_{dis}^{max}(t) \geq P_{out}(t) \geq P_{chg}^{max}(t), \\ P_{chg}^{max}(t) & P_{out}(t) \leq P_{chg}^{max}(t) \end{cases} \tag{14}$$

Table 2: EV power consumption model parameters.

Parameter	Definition	Value
V	Vehicle speed in meters per second	
V_{mph}	Vehicle speed in miles per hour	
ρ	Air density (kg/m^3)	1.225
A_{veh}	Vehicle front area (m^2)	2.27
C_d	Drag coefficient	0.28
α_{dr}	Drivetrain coefficient 1	0.004
β_{dr}	Drivetrain coefficient 2	0.5
γ_{dr}	Drivetrain coefficient 3	29.3
c_{dr}	Drivetrain coefficient 4	375
c_{rr}	Rolling resistance coefficient	0.0075
m	Vehicle mass (kg)	1520
g	Gravity (m/s^2)	9.81
θ	Road grade	0
Δt	Discrete time step (s)	1
β_{eff}	Battery to motor efficiency	0.85
β_{rbs}	Regeneration efficiency	0.4
$P_{\max}$	Maximum power output (W)	100,000
$P_{\min}$	Minimum power loss or maximum regeneration/recharging power gain (W)	−7,000

Table 3: Battery equivalent circuit model parameters.

Parameter	Definition	Value
N_s	Number of cells in series in each module	96
N_p	Number of parallel modules	2
N_t	Total number of cells in battery pack	192
$V_{OC}(t)$	Cell open-circuit voltage at time t (V)	Using lookup-table
$R_{\mathrm{int}}(t)$	Cell internal resistance at time t (Ω)	Using lookup-table
$I_{\mathrm{cell}}(t)$	Cell current at time t (A)	$I_{\mathrm{cell}}(0) = 0$
$V_{\mathrm{cell}}(t)$	Cell terminal voltage at time t (V)	
$V_{\mathrm{out}}^{\min}$	Minimum battery terminal voltage (V)	336
$V_{\mathrm{out}}^{\max}$	Maximum battery terminal voltage (V)	403.2
$P_{\mathrm{out}}(t)$	Battery power requirement at time t (W)	
$\widetilde{P}_{\mathrm{out}}(t)$	Actual battery power output at time t (W)	
$P_{\mathrm{dis}}^{\max}(t)$	Maximum battery power output while discharging at time t (W)	
$P_{\mathrm{chg}}^{\max}(t)$	Maximum battery power input while charging at time t (W)	
$I_{\mathrm{rate}}(t)$	C-rate at time t	
K_{cell}	Rated cell capacity (Ah)	33.1
$\delta_{\mathrm{soc}}(t)$	Battery state-of-charge at time t	
δ_{soh}	Battery state-of-health	
Δt	Discrete time step (seconds)	1

$$I_{\mathrm{cell}}(t) = \frac{\widetilde{P}_{\mathrm{out}}(t)}{V_{out}^{c}(t) \cdot N_s} \cdot N_p, \qquad I_{\mathrm{rate}}(t) = \frac{I_{\mathrm{cell}}(t)}{K_{\mathrm{cell}} \cdot \delta_{\mathrm{soh}}}, \tag{15}$$

$$\delta_{\mathrm{soc}}(t) = \delta_{\mathrm{soc}}(t-1) - I_{\mathrm{rate}}(t) \cdot \Delta t. \tag{16}$$

2.4. Battery Degradation Model. Battery degradation is affected by several factors such as battery temperature, SOC, C-rate, and total current throughput (Ah-throughput) [48]. Some models approximate the total Ah-throughput as a product of constant depth-of-discharge and the number of cycles [23]; thereby, ignoring the effects of SOC and C-rate. This framework adopts a semiempirical battery degradation model proposed by Wang et al. [21] that includes three important parameters: time (or battery age), temperature, and C-rate. It computes calendar aging ($\mathbf{Q}_{\mathrm{cal}}$) as a function of time (τ) and temperature ($\mathbf{T}$) and cycle aging ($\mathbf{Q}_{\mathrm{cyc}}$) as a function of temperature, C-rate ($\mathbf{I}_{\mathrm{rate}}$), and lifetime Ah-throughput ($\mathbf{I}_{\mathrm{ah}}$). The model parameters are fitted using experimental aging data for high-power density 1.5 Ah, 18650 cylindrical cells with $LiMn_{1/3}Ni_{1/3}Co_{1/3} + LiMn_2O_4$ (NCM + LMO) cathode and a graphite anode. Their results indicate that the predicted values are within ±5% of the measured battery capacity loss. The model can be expressed as equations (17)-(19).

$$Q_T = Q_{\mathrm{cal}} + Q_{\mathrm{cyc}}, \tag{17}$$

$$Q_{\mathrm{cal}} = f\tau^{0.5} \cdot \exp\left(-\frac{E_a}{RT}\right), \tag{18}$$

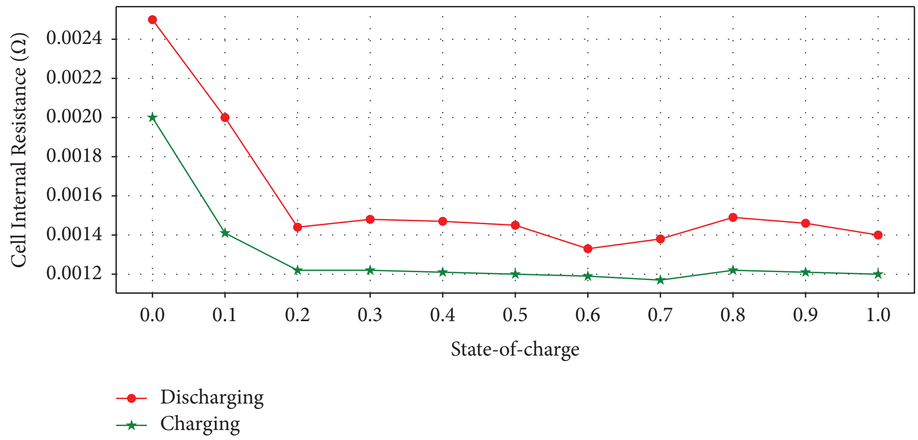

Figure 1: Cell internal resistance values at different SOC.

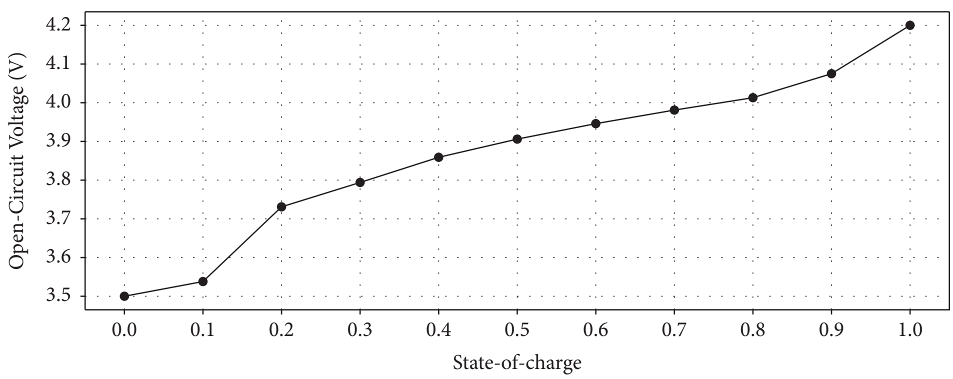

Figure 2: Cell open-circuit voltage values at different SOC.

$$Q_{\mathrm{cyc}} = \left(aT^2 + bT + c\right) \cdot \exp\left[(dT + e) \cdot I_{\mathrm{rate}}\right] \cdot I_{\mathrm{ah}}. \tag{19}$$

To account for the variable C-rate and temperature, the model is modified by taking the differentiating total capacity loss function with respect to a discretized time step ($\Delta\tau$). For each time step, the current flow is assumed to be constant, and instantaneous capacity loss (D_T) is computed as the sum of instantaneous capacity loss D_{cap} and instantaneous cycle loss D_{cyc} by taking the differential of their respective functions. The sum of instantaneous capacity loss is updated to get the total capacity loss until the battery replacement threshold limit (δ_{rep}) is reached. Hence, the battery lifespan is equal to the number of days elapsed before the total capacity loss reaches the specified threshold limit. Because Reference [49] has a rated nominal cell capacity of 33.1 Ah and the data are calibrated for 1.5 Ah cells, a correction factor (β_{corr}) equal to the ratio of rated nominal capacities is multiplied by the cycle loss. Equations (20)-(22) describe the modified model, and Table 4 shows the parameter values.

$$D_T = D_{\mathrm{cal}} + D_{\mathrm{cyc}}, \tag{20}$$

$$D_{\mathrm{cal}} = 0.5\, f\tau^{-0.5} \cdot \exp\left(-\frac{E_a}{\mathrm{RT}}\right), \tag{21}$$

$$D_{\mathrm{cyc}} = \left(aT^2 + bT + c\right) \cdot \exp\left[(dT + e) \cdot I_{\mathrm{rate}}(\tau)\right] \cdot I_{\mathrm{cell}}(\tau) \cdot \beta_{\mathrm{corr}}. \tag{22}$$

This model uses ambient temperature as a proxy for battery temperature, thereby assuming that the thermal effects on internal resistance and cell current are negligible. This assumption can be addressed by including a suitable electrochemical-thermal model in the framework (see Reference [50] for a review) or by using a 1D lookup table to link battery temperature with the environment temperature and battery cell characteristics (e.g., [51, 52]. The model parameters are calibrated for discharging current only. Thus, it is assumed that charging and discharging will have a similar impact on cycle aging based on the absolute value of I_{rate}.

3. Data: Case Study

A case study is presented using the proposed framework for the city of Indianapolis, Indiana, U.S. Real-world household vehicle travel pattern data were extracted from U.S. National Household Travel Survey (NHTS) of 2009 [38]. The NHTS dataset contains 1-day travel diary data of 821 vehicles (with vehicle type as “car”) in the state of Indiana. The key variables of the NHTS dataset include household ID, vehicle ID,

Table 4: Battery degradation parameter values and units.

Parameter	Value and unit	Parameter	Value and unit
a	8.61 $e-$ (1/Ah-K^2)	I_{ah}	Lifetime current throughput (Ah)
b	−5.125 $e-$ (1/Ah-K)	$I_{\mathrm{rate}}(\tau)$	C-rate at time τ
c	0.7629 (1/Ah)	$I_{\mathrm{cell}}(\tau)$	Cell current at time τ (A)
d	−6.7 $e-3$ (1/K-(C-rate))	β_{corr}	1.5/33.1
e	2.35 (1/(C-rate))	E_a	24500 (J/mole)
f	14876 (1/$\mathrm{day}^{0.5}$)	R	8.314 (J/K-mole))
τ	Time (in days)	T	Temperature (K)
$\Delta\tau$	Discretized time step (in days)	δ_{rep}	30%

vehicle type, trip departure time, trip arrival time, and trip travel time for all trips made by the household in a single day. Since most affordable EVs have a driving range of about 80-100 miles, vehicles with trip distances exceeding 80 miles for any single trip are excluded from the analysis to avoid situations with EVs running out of battery in the middle of a trip. In the preliminary data analysis, we observed that several vehicles having longer total daily distance did not have sufficient time between trips to recharge the battery. Thus, based on our preliminary data inspection, we also excluded vehicles with total daily distance exceeding 120 miles from the analysis. These distance-based exclusion criteria reduced our dataset to 760 vehicles. A microscopic traffic simulation model is created to generate realistic drive cycles for the vehicles using the simulation software Aimsun [53]. A detailed road network of Indianapolis containing all major freeways, most urban roads, and some minor roads is built in AIMSUN (see Figure 3). A dynamic 15-minute time period origin-destination traffic demand matrix is simulated for a 24-hour time horizon with an additional 1-hour warm-up period. The traffic demand is calibrated using NHTS trip data for Indiana. The departure time period, distance traveled, travel time, and speed profile of each simulated vehicle are recorded. We generated 41,736 unique simulated drive cycles. Each NHTS trip is matched to a simulated drive cycle which has the least Euclidean distance in terms of both trip distance and average speed. NHTS households with missing simulated drive cycle data for any number of trips are excluded from the analysis. Since most affordable EVs have a driving range of about 80-100 miles, vehicles with a trip distance exceeding 80 miles for any single trip or total daily distance exceeding 120 miles are also excluded. In the end, a total of 3,225 trips made by 697 vehicles were analyzed. Most parameter values in the battery equivalent circuit model and degradation model are taken for Reference [43] with a 24 kWh Li-ion battery. The battery degradation threshold is taken as 30%, that is, the battery is considered to be unusable once its SOH is 70%. Daily average temperature values for Indianapolis in the year 2018 (see Figure 4) are used in a loop to compute both calendar and cycle aging [54]. Since degradation computation is performed for each time step, it allows the use of higher resolution temperature data (e.g., hourly temperature) for more accuracy. Due to data limitations, it is assumed that household vehicle travel patterns remain unchanged until the end of useable battery life. This assumption can be relaxed with the availability of a richer travel pattern dataset. The vehicle is assumed to be fully charged to its SOH level at the start of every day. Opportunistic charging behavior is assumed during the day with a constant charging power of 7 kWh.

Figure 3: Road network of Indianapolis, U.S., used in the simulation.

4. Results and Discussion

The impacts of driving behavior and travel patterns on battery lifespan are analyzed using the proposed multi-paradigm modeling framework. Figure 5 shows the daily distance traveled distribution for the case study data. More than 80% of households travel less than 50 miles per day. Using simulated drive cycles allows the analysis of heterogeneity in driving behaviors such as average speed and speed deviation. The average speed and speed deviation for all households' combined daily drive cycles of all trips are illustrated in Figure 6. The population means of average speed and speed deviation are 37.9 mph and 16.4 mph, respectively.

Most automobile manufacturers offer battery warranties based on either battery age, total distance traveled, or their

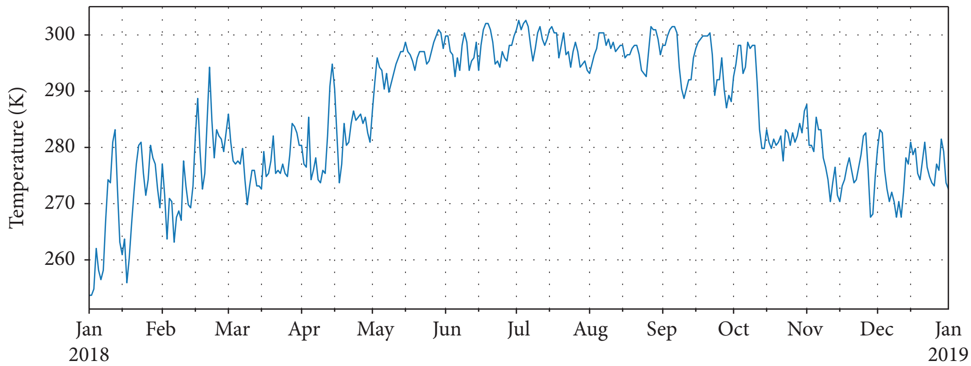

Figure 4: Daily average temperature values for Indianapolis, U.S., in 2018.

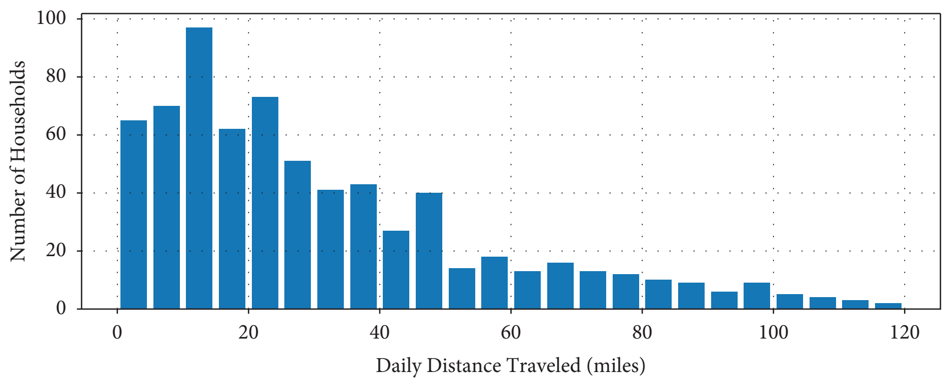

Figure 5: Daily distance traveled distribution.

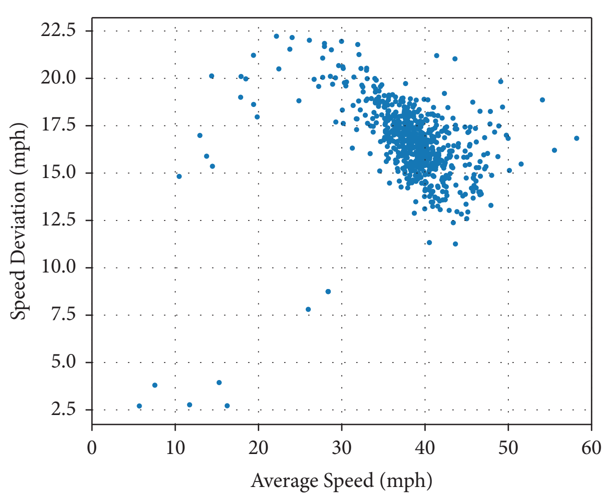

Figure 6: Speed deviation vs. average speed for combined daily drive cycles of households.

combination as a threshold. For example, Reference [46] covers the necessary repairs needed to return battery capacity to about 75% of the original capacity for a period of 5 years or 60,000 miles, whichever comes first [49]. The case study analysis results indicate that almost 50% of the batteries reach their SOH threshold within 5 years and 90% within 8 years. The useable battery lifespan distribution is illustrated in Figure 7. In terms of total distance traveled before EOL, the 50% and 90% quantiles for battery lifespan are approximately 44,500 miles and 72,500 miles, respectively.

To analyze the impact of driving behavior, the average speed and speed deviation for each household are classified as "higher" or "lower" groups based on their value compared to their respective population means. The results indicate that there is little or no difference between the higher and lower average speed groups for the same total distance traveled before EOL (see Figure 8). On the contrary, an

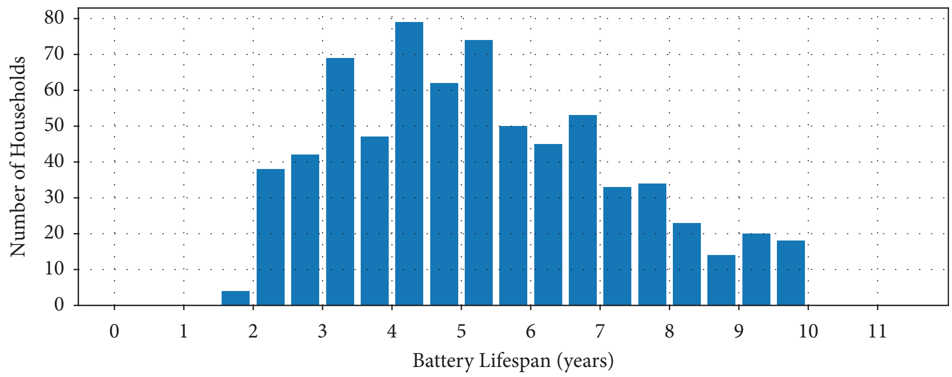

Figure 7: Useable battery lifespan distribution.

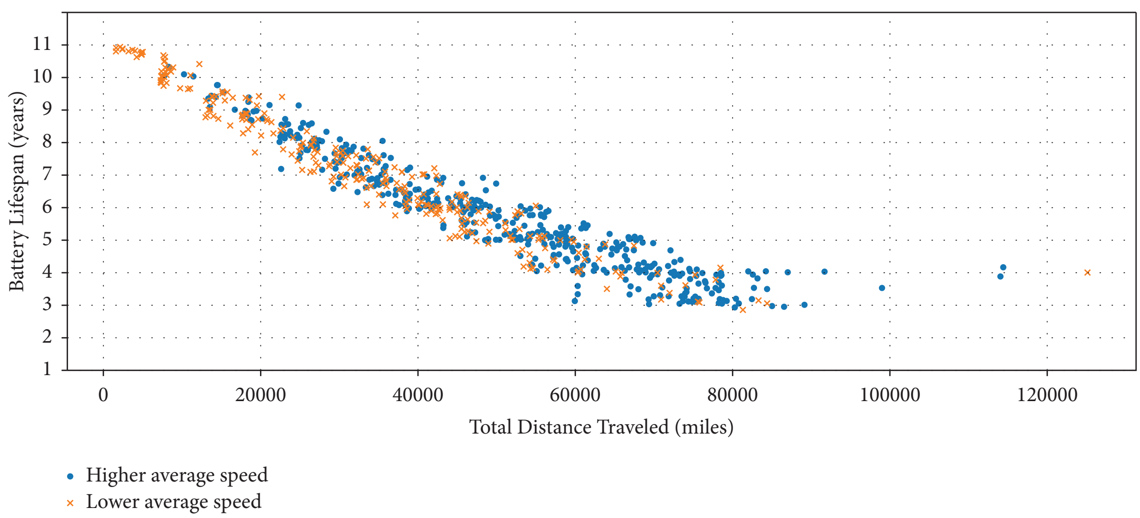

Figure 8: Battery lifespan vs. total distance traveled for average speed-based classification.

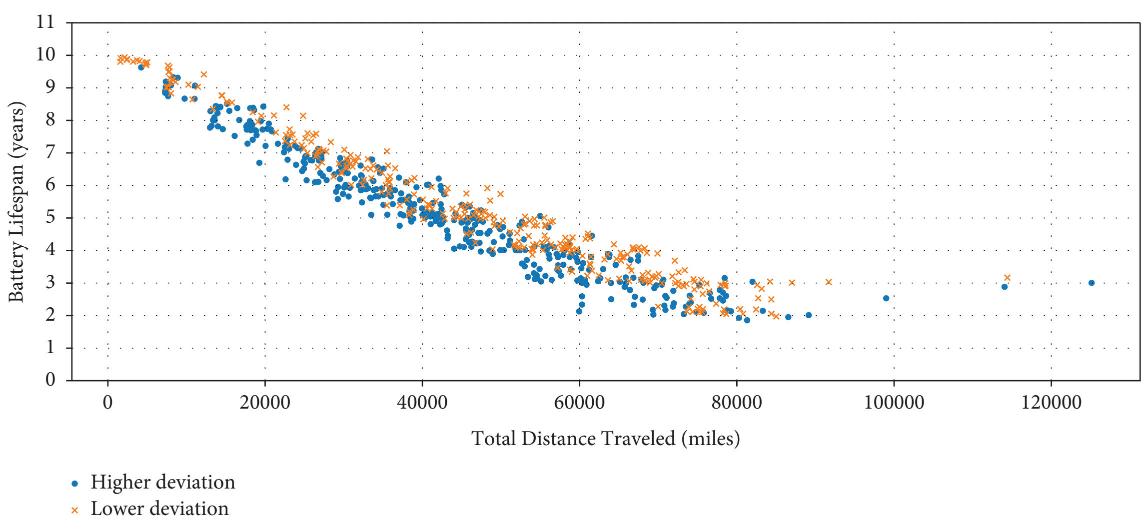

Figure 9: Battery lifespan vs. total distance traveled for speed deviation-based classification.

apparent decrease in battery lifespan can be observed among households with higher speed deviation than those of lower speed deviation (see Figure 9). A higher speed deviation entails more fluctuations in kinetic energy due to acceleration and deceleration (see Section 2.2), which increases the vehicle's overall power consumption. Hence, the difference in lifespan is caused by this additional amount of power required, and thereby, the current flows through the battery to balance the fluctuating kinetic energy at variable speed. These findings illustrate the importance of using realistic and diverse drive cycles over combinations of standard driving schedules to account for differences in driving behaviors.

5. Concluding Comments

This study presents a multiparadigm modeling framework to quantify the useable battery lifespan of a large population of EVs. The inclusion of a microscopic traffic simulation model in the framework enables the analysis of driving behavior heterogeneity in battery lifespan estimation. Each building block of the multiparadigm approach provides the flexibility to include newer models or real-world cases without affecting the framework structure. For example, the traffic simulation model can be replaced by real-world vehicle speed data if such data are available. This study uses the vehicle and battery specifications of Reference [49] in the case study, but the proposed framework can be used to assess other EVs, such as e-rickshaws, by changing the parameter values accordingly. The impacts of vehicle travel patterns and driving behavior (e.g., speed deviation) on EV battery lifespan under regional temperature trends can provide useful information for vehicle owners, policymakers, and vehicle manufacturers. The framework can be used by vehicle owners to assess the lifetime cost of EV ownership, including battery maintenance cost, insurance cost, and battery resale value, based on their travel needs, driving behavior, and geographic location. In addition, policymakers can use battery lifespan distribution for regional temperature and traffic conditions to design incentive strategies, such as tax credits and extended battery warranties, to regulate EV adoption trajectories. It allows vehicle manufacturers to factor in regional conditions and consumer driving behaviors while evaluating the performance and economics of different batteries by modifying the battery equivalent circuit model and degradation model accordingly. The proposed framework can be utilized to enhance EV research applications such as battery management strategies (e.g., maximum/minimum SOC range) to enhance battery lifespan, battery recharging strategies, vehicle-to-grid applications, etc., by including realistic vehicle travel patterns and driving behavior. Furthermore, there is an ongoing argument among researchers to promote electric-powered autonomous vehicles (AVs) over gasoline-powered AVs to limit greenhouse gas emissions and mitigate negative environmental impacts. The proposed framework can be used to assess the battery life and, thereby, life cycle environmental impacts of a large population of electric-powered AVs. This research can be extended in different directions. The first potential future research direction is to integrate the electrochemical-thermal effects into the battery degradation model. This integration enables for more accurate battery health state monitoring as it accounts for the external measurements of terminal voltage, applied current, and surface temperature of the battery [13, 55, 56]. The second research direction is to compare the effects of travel patterns on fuel consumption between EVs and traditional internal combustion engine vehicles. The third research direction is to consider the battery degradation model for different types of batteries used in EVs. The battery degradation of different EV batteries varies based on the charging/discharging rate, number of cycles, and temperature. The detailed information for some recent battery technology is presented by Zhao et al. [57] and Mathieu et al. [58]. The disaggregate battery degradation model should be calibrated for each type of EV to increase the accuracy of the results.

Data Availability

The data used to support the findings of this study are available on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

An Optimization Model for Structuring a Car-Sharing Fleet Considering Traffic Congestion Intensity

Parisa Ahani,[1] **Amilcar Arantes**,[2] **and Sandra Melo**[3]

[1]*CERIS, MIT Portugal Program, Sustainable Energy Systems, Instituto Superior Tecnico, Universidade de Lisboa, Lisbon, Portugal*
[2]*CERIS, Instituto Superior Tecnico, Universidade de Lisboa, Lisbon, Portugal*
[3]*CEiiA, Center of Engineering and Development, Matosinhos, Portugal*

Correspondence should be addressed to Parisa Ahani; prsahani1@gmail.com

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Ever-growing mobility and traffic congestion within urban areas make the need for a sustainable form of transport inevitable. Traffic congestion has a significant effect on the amount of energy consumption of a vehicle and, as a result, on its associated environmental impacts. Any decision-making regarding structuring a fleet without taking into account the traffic congestion level (TCL) will lead to a less sustainable fleet with higher environmental and economic costs. To address this issue, this study examines the effects of the traffic congestion intensity level on the fleet structure of an urban car-sharing company over a certain planning period. We present a new optimization framework for finding an optimal vehicle composition of the fleet of an urban car-sharing company considering the energy consumption of vehicles at different traffic congestion levels. The results show that electric vehicles (EVs) are more competitive than diesel vehicles (DVs) in high-peak traffic congestion from the outset of the planning period. In addition, we perform a sensitivity analysis to take into account the effects of specific uncertain parameters such as the energy and purchasing costs of EVs on the total cost of ownership. As expected, the purchasing price of EVs, energy prices of DVs, and increase in diesel prices have the highest impact on the total cost.

1. Introduction

The idea of several people sharing the same car can be traced back several decades ago [1]. Car-sharing is a type of shared mobility that offers renting cars on a needed basis for as little as 10 minutes [2] and often by the hour when other modes of transport are not available or are not suitable [3]. The users can be passengers, companies, and public agencies [4]. The station of car-sharing is usually close to the location of transportation modes, and the payment is based on travel distance or time spent [4].

Car-sharing has the potential to reduce vehicle use, ownership, and delays in car purchases [5–7]. It is seen as a solution to address the issues of congestion, pollutants, and the occupancy rate of vehicles within urban areas [8, 9]. This leads to increasing urban sustainability from environmental, economic, and societal points of view worldwide. [10–13]. Chen and Kockelman [14] estimated a reduction of 51% in energy consumption and greenhouse gas (GHG) emissions for what they have defined as a “good candidate for shared mobility.”

In two studies [10, 11], the authors conducted a survey of members of a car-sharing club in the US, looking specifically at the impacts of car-sharing on household vehicle ownership. The results showed that the rate of vehicle ownership among club members decreased from 0.47 to 0.24 vehicles per household. In the last decade, the car-sharing market in Europe has expanded, and in Germany, as the largest car-sharing market in Europe, an increase in user usage from 0.26 million in 2012 to 1.29 million in 2020 was reported by Roblek et al. [15].

Various research studies have shown that the demand for car-sharing as a means of mobility in any form is increasing worldwide [16–19]. In many countries around the world, car-sharing or short-term auto access [20] is known as a system to minimize ownership transportation costs and the negative effects of car use. The car-sharing industry has recently significantly increased its market [21, 22]. In the past decade, advancements in communication technologies and smartphone applications have led to the emergence of car-sharing companies such as DriveNow and Car2Go. Autolib in Paris is one of the known operators in car-sharing systems that offers electric car-sharing services with at least 1750 electric vehicles (EVs) and 65,000 members. Such companies own a number of vehicles and deal with any cost related to the operation of their fleet in the car-sharing service.

There is a trend toward the use of electric vehicles such as gasoline-electric hybrids and electric vehicles in car-sharing systems [20, 23]. EVs, in comparison to their conventional counterparts, have lower operational and maintenance costs, and their zero tailpipe emissions are another option for operation in car-sharing services since they usually operate in urban environments. Furthermore, with regard to energy consumption, their performance at lower speeds is better than that of internal combustion engine vehicles (ICEVs) [24], which is an additional advantage during peak-hour traffic. The purchase price of EVs has thus far been the main barrier to their wider use. However, with increasing technological advancement, the cost of EV batteries, which makes up a large portion of the price of an EV, has been on a downward trend in recent years. Following Nykvist et al. [25]; the battery price decreased by 77% from 2007 to 2018, reaching an average cost of $230 per kWh. Thus, this downward trend in battery prices will lead to a reduction in EV purchase prices over time. In contrast, ICEVs have lower purchase prices. However, the fuel cost of an ICEV, which is the major cost during the lifetime of such a vehicle, is very unpredictable. The steep increase in oil prices and their wild fluctuations in recent years have affected the fuel cost of ICEVs. Accordingly, any decision for vehicle replacement based merely on the actual total cost of ownership of a vehicle without taking into account the concerned uncertainties might increase the cost in the long term.

To the best of our knowledge, no research study has been conducted on an optimal fleet replacement for a car-sharing service considering traffic congestion levels. This study introduces a new optimization framework to assist a car-sharing company in selecting the best investment strategy for structuring its fleet from different types of vehicle technology (EVs vs. ICEVs in particular) over a certain planning time period. The novelty of the developed framework lies in considering different traffic congestion intensity levels and various demand levels for a car-sharing service throughout a typical day of operation. The optimization framework will provide the operator with the best fleet composition for its car-sharing company over a certain planning period.

The remainder of the paper is organized as follows: Section 2 contains a literature review, and Section 3 describes the model and the optimization framework. In Section 4, the data and assumptions are presented, and Section 5 is dedicated to the results and discussion. The paper ends in Section 6 with the enunciation of some conclusions.

2. Literature Review

Various research studies have focused on fleet optimization for shared mobility systems [26–31]. In a study by Wallar et al. [28], the authors provided a model for optimizing fleet composition to distributions of vehicles for shared mobility service. They proposed an algorithm for determining the required number of vehicles, where they should be located at the start point, and how they should be routed to satisfy all travel demands in a particular period of time while enabling many passengers to be served by the same vehicle. Based on an analysis of historical taxi data from Manhattan in New York City, they presented a model estimating the number of required passenger cars to meet all daily taxi demands, with an average waiting time and an extra travel delay. Monteiro et al. [26] provided a model to optimize the fleet size by maximizing the number of served clients to satisfy the demand while minimizing the high number of parked vehicles in the station using a mixed-integer linear program. Nair and Miller-Hooks [29] presented an optimization model for fleet management of shared-vehicle services by using a stochastic mixed-integer program with joint chance constraints and random demand across stations to minimize cost car redistribution in a fleet.

Some research studies developed optimization models for electric mobility in car-sharing systems [32–36]. In another study by [32], the authors performed an extensive review of recent literature on car-sharing. They developed an optimization framework for the fleet composition of station-based car-sharing systems with heterogeneous fleets by considering three different types of vehicles: ICEVs, plug-in hybrid electric vehicles (PHEVs), and EVs. They demonstrated that existing infrastructure and well-established technology help ICEV growth and make PHEVs the best alternative compared to the other two types of vehicles. They concluded that EVs remain the best alternative considering environmental and global emissions and local pollutants, especially over long-term periods. In a research study by Bubeck et al. [34]; the authors analyzed the total ownership cost of electric mobility by considering the CO_2 subsidies offered to EVs and buyer premiums as an incentive on the German road up to 2050. The results showed that full and mild hybrid electric vehicles are currently more economical even without government subsidies. Moreover, they showed that buyer premiums are necessary to make EVs competitive in terms of cost, and from 2030 onward, EVs can survive as an economical option.

Although there have been various research studies focusing on fleet optimization in shared mobility and car-sharing systems, to the best of our knowledge, no research study has addressed optimizing car-sharing fleet structure considering the effect of traffic congestion. In this study, motivated by research studies on the fleet replacement problem in Urban Freight Transport (UFT) (see [37, 38], and [39], we introduce a novel optimization framework to assist a car-sharing company in choosing the best investment strategy for having different types of vehicles (in particular EVs vs. ICEVs) in its fleet over some planning time period. Despite some similarities between vehicle replacement in urban freight and car-sharing, there are differences between these two types of problems, which each deserve their own analysis. This work focuses on vehicle composition for car-sharing companies, whereas the focus of previous research studies has been on vehicle composition for UFT. The nature of the demand for urban freight transport throughout the day is different from that of car-sharing services. There are limitations regarding the operation of freight vehicles within a city during the day (in particular, during peak hours). However, there are no such restrictions in regard to passenger vehicle operations within urban areas. More importantly, the developed optimization framework takes into account the magnitude of traffic congestion, which is a novel approach even within the context of UFT.

3. Research Methodology

The aim of this research is to determine the best combination of different types of passenger vehicles for the fleet of a car-sharing company over a certain planning period. There are various vehicles of different types that can be used by a company to run its car-sharing service. Each vehicle has its own characteristics, which affect the associated costs. These costs include the purchase price, energy costs, operation and maintenance costs, and emission costs, to name the most important ones. In addition, depreciation rates for vehicles vary greatly, and accordingly, the corresponding salvage revenues are of various magnitudes.

Energy consumption is one of the main costs associated with a vehicle during its lifetime. Speed is a principal factor affecting the energy consumption of a vehicle and, as a result, the amount of emissions that the vehicle produces. Following He et al. [40], the optimal fuel consumption occurs in the speed range of 45–80 km/h, whereas EVs have lower energy consumption in the range of speeds between 20 km/h and 40 km/h [41]. On the other hand, during peak hours, traffic congestion affects the speed of a vehicle. In congested areas, vehicles are faced with frequent stopping and going and operating in lower-level gears, which makes them consume more energy. Therefore, the developed optimization framework considers these important factors by dividing a typical day of operation into several blocks of time depending on the traffic congestion level of that day. The idea of dividing a typical day of the planning time period into several blocks of time was motivated by previous research studies on electricity supply planning Huang and Wu [42] and Wu and Huang [43]. To demonstrate the idea of dividing a typical day of operation into different blocks of time, we use the data regarding the average speed given during 22 hours of a day in Ji et al. [44], where the authors presented the average speed of 20,000 taxi datasets recorded by GPS in part of the city of Shenzhen in China for 22 hours from 1 AM to 11 PM on a weekday. An average speed of less than 30 km/h can be demonstrated more than 70% of the time, with the sharpest decline in average speed occurring during the peak hours of 6–8 AM and 4–6 PM.

Thus, based on the average speed given there and the amount of consumption for the corresponding velocity given by He et al. [40] and Grée et al. [41]; we illustrate in Figure 1 how a typical day of operation is divided into three blocks of low, medium, and high congestion levels.

The developed optimization framework will determine a more sustainable car-sharing fleet structure for the company over a certain planning period while satisfying the interests of the concerned stakeholders. In addition, uncertainties related to various parameters such as energy, purchase, emission, and maintenance costs need to be addressed. These uncertainties have an impact on the total cost of running a car-sharing service, and any decisions regarding the composition of the fleet taken without considering these can result in extra costs for the company. Accordingly, we perform a sensitivity analysis to analyze the effects of a number of uncertain input parameters on the total cost.

3.1. Mathematical Optimization Framework. The mathematical optimization framework for structuring the fleet of a car-sharing company considering traffic congestion levels over a certain planning period is presented and discussed in this subsection. The formulation is adapted and expanded from the optimization framework in Feng and Figliozzi [37]; which was developed for the fleet composition of an urban freight transport company. Since the traffic congestion level is an important and effective factor in minimizing the total cost within the context of car-sharing services, the previously developed framework needs to be adapted to take such a factor into consideration.

These indices are used throughout the paper as follows:

(i) $K \in k = \{1, \cdots, K\}$ represents each type of vehicle technology
(ii) $i \in A = \{0, \cdots, A_k\}$ represents the age of a vehicle of type k
(iii) $t \in T = \{0, \cdots, T\}$ represents the year of the planning time period
(iv) $s \in S = \{1, \cdots, S\}$ refers to the level of traffic congestion in a day

The decision variables are as follows:

(i) $X_{i,t,k}$: number of age i type k vehicles used in year t
(ii) $Y_{i,t,k}$: number of age i, type k salvaged vehicles at the end of year t
(iii) $Z_{t,k}$: number of new type k purchased vehicles at the beginning of year t
(iv) $x_{i,t,k,s}$: total number of kilometers traveled by vehicles of type k age i during the level of s traffic congestion in year t

The parameters are denoted as follows:

(i) K: number of vehicle types
(ii) T: span of the planning period
(iii) S: level of traffic congestion of a typical day of operation

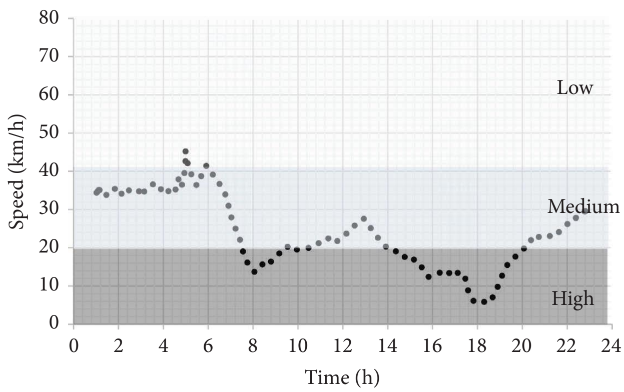

Figure 1: Levels of traffic congestion considering speed and different blocks of time.

(iv) A_k: maximum age of vehicle type k

(v) dr: discount rate for taking into account the devaluation of money with time

(vi) b_t: budget of year t

(vii) $w\ d$: working days in the year

(viii) $d_{t,s}$: demand related to the level of s traffic congestion in year t

(ix) $u_{i,t,k}$: the maximum distance that can be traveled by a vehicle of type k and age i in year t

(x) $v_{k,t}$: purchase cost (€) per unit of type k vehicle during period t

(xi) $s_{i,k}$: salvage revenue (€) of an age i, type k vehicle

(xii) $e_{i,t,k,s}$: per-km energy cost (€/km) of vehicle type k of age i during level s of traffic congestion of year t

(xiii) $m_{i,t,k,s}$: per-km operation and maintenance cost (€/km) of vehicle k of age i during level s of traffic congestion of year t

(xiv) $em_{i,k,s}$: CO_2 emission cost (€/km) of vehicles of age i and type k during level s of traffic congestion

3.1.1. Objective Function. The objective function minimizes the total cost. The total cost is composed of various cost elements, namely, energy, operation and maintenance, purchase, and emission costs. We actualized the costs at the beginning of the planning period. Since the objective function is linear and the decision variables take a nonnegative integer and real values, problem (1) is thus a mixed-integer linear programming problem. Therefore, to minimize the total cost, the following optimization problem is solved as follows:

$$
\begin{aligned}
\operatorname{Min} TC = {} & \sum_{t=0}^{T-1}\sum_{k=1}^{k} v_{k,t} z_{t,k} (1+dr)^{-t} - \sum_{i=1}^{A_k}\sum_{t=0}^{T}\sum_{k=1}^{K} s_{i,k} Y_{i,t,k} (1+dr)^{-t} \\
& + \sum_{i=0}^{A_k-1}\sum_{t=0}^{T-1}\sum_{k=1}^{K}\sum_{s=1}^{S} \left(e_{i,t,k,s} + m_{i,t,k,s} + em_{i,k,s}\right) x_{i,t,k,s} (1+dr)^{-t}, \\
s.t \sum_{s=1}^{S} x_{i,t,k,s} & \le w\ d\, u_{i,t,k} X_{i,t,k} \quad \forall i \in A - \{A_k\}, \quad \forall k \in K, \quad \forall t \in T - \{T\}, \\
\sum_{k=1}^{K}\sum_{i=0}^{A_k-1} x_{i,t,k,s} & \ge d_{t,s} \quad \forall s \in S, \forall t \in T - \{T\}, \\
& \cdot \sum_{k=1}^{K} v_{k,t} z_{t,k} \quad \forall t \in \{0, 1, 2, \ldots, T-1\}, \\
X_{(i-1)(t-1),k} & = X_{i,t,k} + Y_{i,t,k} \quad \forall t \in T, \forall k \in K, \forall i \in A - \{0\}, \\
Z_{t,k} & = X_{0,t,k} \quad \forall t \in T, \forall k \in K, \\
X_{i,T,k} & = 0 \quad \forall k \in K, \forall i \in A - \{0, A_k\}, \\
X_{A_k,t,k} & = 0 \quad \forall t \in T, \forall k \in K, \\
Y_{0,t,k} & = 0 \quad \forall t \in T, \forall k \in K, \\
& \cdot Z_{t,k}, X_{i,t,k}, Y_{i,t,k} \in Z^{+} = \{0, 1, 2, \ldots\},
\end{aligned}
\tag{1}
$$

$x_{i,tk,s} \in R^{+}$, where R^{+} represents the set of nonnegative real numbers.

The total cost (€) associated with the car-sharing service business over the planning period consisted of the following components:

Purchase cost:

$$PC = \sum_{t=0}^{T-1}\sum_{k=1}^{K} v_{k,t} Z_{t,k} (1 + \mathrm{dr})^{-t}. \tag{2}$$

Salvage revenue:

$$SR = \sum_{i=1}^{A_k}\sum_{t=0}^{T}\sum_{k=1}^{K} s_{i,k} Y_{i,t,k} (1 + \mathrm{d}r)^{-t}. \tag{3}$$

Energy cost:

$$EC = \sum_{i=0}^{A_k-1}\sum_{t=0}^{T-1}\sum_{k=1}^{K}\sum_{s=1}^{S} e_{i,t,k,s} x_{i,t,k,s} (1 + \mathrm{d}r)^{-t}. \tag{4}$$

Operation and maintenance cost:

$$OP\,\&\,MC = \sum_{i=0}^{A_k-1}\sum_{t=0}^{T-1}\sum_{k=1}^{K}\sum_{s=1}^{S} m_{i,t,k,s} x_{i,t,k,s} (1 + \mathrm{d}r)^{-t}. \tag{5}$$

Emission cost:

$$EmC = \sum_{i=0}^{A_k-1}\sum_{t=0}^{T-1}\sum_{k=1}^{K}\sum_{s=1}^{S} em_{i,k,s} x_{i,t,k,s} (1 + \mathrm{d}r)^{-t}. \tag{6}$$

Constraint (2) concerns the total distance (in kilometers) traveled in any year, which cannot be greater than the maximum distance traveled by all types of vehicles used. In addition, in constraint (3), the distance traveled by all vehicles of any type and age for each demand level in any year must be greater than the demand for the corresponding level of s traffic congestion in that year. Constraint (4) shows that the company has a yearly limited budget for purchasing new vehicles. Constraint (5) enforces that in any year of the planning period, the number of vehicles used and salvaged of any type must be equal to the number of vehicles used of the same type in the preceding year. Constraint (6) ensures that in any planning period year, the new vehicles of any type introduced into the fleet must be the same as the number of purchased vehicles of that type. Constraint (7) forces all remaining vehicles to be sold at the end of the planning time period. Constraint (8) ensures that when a vehicle reaches its maximum age, it must be salvaged. Constraint (9) ensures that new vehicles cannot be salvaged immediately. Lastly, in constraint (10), decision variables $Z_{t,k}$, $X_{i,t,k}$ and $Y_{i,t,k}$ can take only non-negative integer values, and $x_{i,t,k,s}$ can also take nonnegative real values.

4. Data and Assumptions

For the numerical experiments, we assume that a car-sharing company has the goal of deriving an optimal combination of its fleet from two available types of diesel and electric vehicles both with the same passenger capacity. These two types are denoted as $k = 1$ and $k = 2$ for DVs and EVs, respectively. Tax incentives for diesel (https://taxfoundation.org/gas-taxes-europe-2019/) cars, better fuel economy in most European countries, and lower tailpipe emissions of CO_2 for diesel (https://autotraveler.ru/en/spravka/fuel-price-in-europe.html) [45] compared to gasoline are the main reasons for choosing this type of ICEV in our numerical experiments. The data regarding the two types of vehicles and other input parameters are given in Table 1.

With regard to the lifetime of vehicles, considering the European Automobile Manufacturers Association (https://www.aut.fi/en/frontpage_vanha/statistics/international_statistics/average_age_of_passenger_cars_in_some_european_countries), which has reported an age of 8 years for passenger cars in some European countries, and following Mahut et al. [46]; we consider a lifetime of 8 years for both passengers DVs and EVs. In addition, a discount rate of 5% [47] is used. By considering the foreseen daily utilization and EV battery lifetime of 160,000 km [48, 49], each EV will need two batteries over its eight-year operational lifetime. We include the discounted cost of the extra battery in the EV purchase price.

For the range limitation of EVs, the Nissan Leaf, the electric car model that registered the highest number of sales in Europe in 2018 and the third leading passenger electric vehicle in 2020 (https://www.statista.com/statistics/965507/eu-leading-passenger-electric-vehicle-models/), was the EV analyzed in this study. The Leaf has a range of 264 kilometers with one full charge of battery. (https://www.nissanusa.com/vehicles/electric-cars/leaf/features/range-charging-battery.html).

To calculate the salvage or resale value, we use the following formula proposed by Feng and Figliozzi [37]:

$$s_{i,k} = (1 - \theta_k) s_{(i-1)k} = v_k (1 - \theta_k)^i, \quad \forall k \in K, \forall i \in A - \{1\}, \tag{7}$$

where θ_k is the rate at which vehicle type k is depreciated. Based on the values reported by Messagie et al. [50], we set depreciation rates per year of 17% and 28% for DVs and EVs, respectively.

For the medium TCL, we use an energy consumption of 0.062 lit/km [51] and 0.145 kWh/km [52] for DVs and EVs, respectively.

Based on the data given in Table 2, the energy costs per kilometer are calculated using the formulas presented in the following equations:

$$e_{i,t,s,1} = R_{s,1}\left(\frac{\text{lit}}{\text{km}}\right) \times G_{dv} \times e^{\widehat{f}_1 \cdot t} \quad \forall i \in A\, \forall t \in T\, \forall s \in S = \{1, 2, 3\}, \tag{8}$$

$$e_{i,t,s,2} = Q_{s,2}\left(\frac{kWh}{km}\right) \times H_{ev} \times e^{\widehat{f}_2 \cdot t} \quad \forall i \in A - \{1\}\, \forall t \in T\, \forall s \in S = \{1, 2, 3\}, \tag{9}$$

Table 1: Input-parameter data.

Vehicle type	DVs	EVs
Lifetime (years)	$A_1 = 8$	$A_2 = 8$
Discount rate (%)	0.05	0.05
Annual use (km)	40000	40000
Daily use (km)	160	160
Planning time horizon (years)	16	16
Depreciation rate (%)	0.17	0.28
Energy cost growth rate (Pordata 2018) (%)	0.0582	0.0289
Purchase cost (Nissan, 2020) (€)	14000	28000
Energy consumption in low TCL (s_1)	0.0465 lit/km	0.1087 kWh/km
Energy consumption in medium TCL (s_2)	0.062 lit/km	0.145 kWh/km
Energy consumption in peak TCL (s_3)	0.0775 lit/km	0.1812 kWh/km
Energy cost (Pordata 2018)	1.16 €/lit	0.16 €/kWh
CO_2 emissions (well-to-wheel)	2.63 kg/lit	0.47 kg/kWh

Table 2: Summary of characteristics of previous studies.

References	Method	Model	Context	Fleet size	Vehicle replacement/ composition problem	TCL
[26]	Opt	Mixed-integer linear programming (MILP)	Car-sharing system	✓	—	—
[27]	Opt	(MILP)	Car-sharing system	✓	—	—
[28]	Opt	Integer linear programming (ILP)	Car-sharing system	✓	✓	—
[29]	Opt	Stochastic mixed-integer program (SMIP)	Fleet management shared-vehicle system	✓	—	—
[32]	Opt	(ILP)	Car-sharing system electric mobility	✓	✓	—
[34]	Survey	Total cost of ownership model	Electric mobility	—	—	—
[31]	Opt	Mixed integer program (MIP)	Shared mobility	✓	—	—
[35]	Opt	(MILP)	Car-sharing system electric mobility	✓	—	—
[36]	Opt	Simulation model	EV- sharing system	✓	—	—
[37]	Opt	(MIP)	Urban freight fleet replacement problem	✓	✓	—
[38]	Opt	(MIP)	Urban freight fleet replacement and composition problem	✓	✓	—
[39]	Opt	Mixed integer quadratic programming (MIQP)	Urban freight fleet replacement problem	✓	✓	—
This research	Opt	(MILP)	Car-sharing system	✓	✓	✓

where $R_{s,1}$ and $Q_{s,2}$ represent the energy consumption per km. G_{dv} and H_{ev} are the corresponding parameters for the energy cost of DVs and EVs as presented in Table 1, and $\widehat{f}_1$ and f_2 are the annual growth rates of 5.82% and 2.89% [39] for diesel and electricity prices, respectively. The price growth rates were defined on the basis of the annual diesel price history from 1980 to 2014 and the electricity price history from 1991 to 2014 in Portugal (https://www.pordata.pt/Portugal).

We should mention that we made the right-hand side of (8) and (9) independent of the age of vehicles (i.e., i). In fact, due to a lack of data regarding the energy consumption of vehicles with age, similar to Feng and Figliozzi [37] and Ahani et al. [39]; we assumed that $R_{s,1}$ and $Q_{s,2}$ are fixed values for each i.

On average, well-to-wheel CO_2 emissions by DV and EV are approximately 2.63 kg/lit and 0.47 kg/kWh, respectively [53]. The CO_2 emission value for EVs is calculated by taking into account the emissions produced by different types of power generation technologies. Therefore, the following equations give the emission cost of each type of vehicle based on its age:

$$\begin{aligned} em_{i,s,1} &= 0.00263\left(\frac{\text{tan}}{\text{lit}}\right) \times R_{s,1}\left(\frac{\text{lit}}{\text{km}}\right) \times ec, \quad \forall i \in A - \{A_k\}, \\ em_{i,s,2} &= 0.47\left(\frac{\text{kg}}{\text{kWh}}\right) \times Q_{s,2}\left(\frac{\text{kWh}}{\text{km}}\right) \times 0.001\left(\frac{\text{ton}}{\text{kg}}\right) ec, \quad \forall i \in A - \{A_k\}. \end{aligned} \tag{10}$$

An *ec* value of €25/ton is considered [54].

Following the maintenance cost data analysis from Carstens [55], each car has a cost of approximately 0.04 euro/km. The mileage and age of a vehicle affect its maintenance cost. The total maintenance cost for EVs is at most 60% of the maintenance cost for ICEVs [50]. Hence, we use the following quadratic functions extrapolated from the data adopted from Carstens [55] to estimate the maintenance costs of ICEVs and then use them to approximate the maintenance costs of EVs.

$$m_{i,1} = -0.0015i^{\wedge}2 - 0.011i + 0.076, \quad \forall i \in A - \{0\},$$
$$m_{i,2} = 0.6\left(-0.0015i^{\wedge}2 - 0.011i + 0.076\right), \quad \forall i \in A - \{0\}. \tag{11}$$

Regarding other input parameters, the following are assumed:

(i) The company has 20 diesel vehicles of different ages in its initial fleet. 12 vehicles of ages 0–3 years with three vehicles of each age and 8 vehicles of ages 4–7 years with two vehicles of each age.

(ii) There are three traffic congestion levels (TCLs): low (s1), medium (s2), and high (s3) with vehicle demands of 20%, 30%, and 50% of the total demand, respectively (i.e., $d_{t,1} = 0.2d_t, d_{t,2} = 0.3d_t, an\ d\ d_{t,3} = 0.5d_t$).

(iii) We assume that both DVs and EVs are used 160 km per day, which is equivalent to 40,000 km per year based on a total of 250 working days in a year.

(iv) An annual budget of 56,000 euros is assumed for purchasing new vehicles.

(v) We assume that the energy consumption of DVs in the low and high TCLs is 25% less and 25% more than that of the medium TCL, respectively.

(vi) We also assumed a scenario without incorporating TCL into the model. For this scenario, we consider the energy consumption of 0.062 lit/km and 0.145 kWh/km for DVs and EVs, respectively.

(vii) During each year, the total demand for car-sharing vehicles is supposed to be equivalent to the total distance traveled by all 20 vehicles in the corresponding year ($d_t = 40,000km \times 20$).

(viii) We assumed that $R_{s,1}$ and $Q_{s,2}$ are independent of age.

5. Results and Discussion

This section presents the results of resolving the mixed-integer linear optimization problem (1) (see Table 3) using the CPLEX solver of GAMS version 27.3 [56] on a laptop computer with CPU Intel core i3–4030U 1.90 GHz and RAM memory of 4 GB running Windows 10 64 bits. We present the total number of purchased vehicles, total distance traveled in each traffic congestion level by each type of vehicle, number of vehicles used, and number of salvaged vehicles in each year of the planning period. An elasticity analysis is also performed to show the magnitude of the effects of certain input parameters on the total cost.

Table 3: Model statistics.

Name	Number
Constraints	745
Variables	1565
Discrete variables	646
Execution time	0.06 seconds

Figure 2 shows the number of vehicles used each year for the two types of vehicles. Regarding the number of vehicles used, the share of electric vehicles in the fleet increases over time up to year 12 of the planning period and then remains constant until year 14 and then begins to decrease. Keeping in mind that the initial fleet has been composed of only DVs, the reason for the increase in the share of EVs and replacing DVs in the fleet is their low operating costs, especially when considering the traffic congestion level, which is a major factor affecting the fuel consumption of a vehicle. We can see that the share of EVs in the fleet begins to decrease after year 14 of the planning period, and the main reasons are their high purchase price and high depreciation rate. Indeed, these two factors mean that EVs, when compared with DVs, are not competitive for just the last two years of the planning time period. Had the planning period been infinite, then the share of EVs would have increased constantly over the course of the said planning period. Additionally, Figure 3 shows the number of purchased DVs and EVs over the 16 years of the planning period. The number of EVs decreases toward the end of the planning period because the depreciation rate for EVs is higher than that of DVs. Figure 4 shows the number of vehicles salvaged at the end of each year and at the end of the planning time period when all vehicles are salvaged due to the end of the operation.

For a more thorough analysis, we present in Figures 5 and 6 the total traveled distance for each type of vehicle and the traffic congestion level. As stated previously, we assume that the initial fleet of the car-sharing service company is made up of DVs only. The figures show that for a high TCL ($s = 3$), the total distance traveled by EVs begins to increase year by year, and from year eight until year fourteen of the planning period, the total traveled distance in this TCL is covered only by EVs. In the case of medium TCL ($s = 2$), albeit in comparison to high TCL with a slower increase in the share of EVs, and only from year 9 to year 13 of the planning period is the entire demand in this TCL met by EVs. DVs remain competitive chiefly for low TCL ($s = 1$), as the operational cost for this TCL is lower than those of the other two levels. As previously mentioned, the increase in the share of traveled distance by DVs for the high and medium TCLs toward the end of the planning period can be attributed to the high purchase price and the high depreciation rate of EVs, which render them less economically viable for just a few years of use in the fleet.

We also assumed a scenario without incorporating the traffic congestion level into the model to show that the traffic congestion level has an important impact on the total cost.

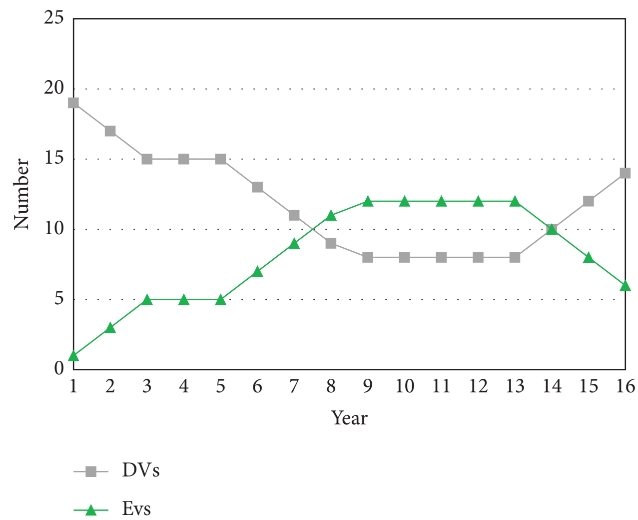

Figure 2: Number of vehicles used during the planning period.

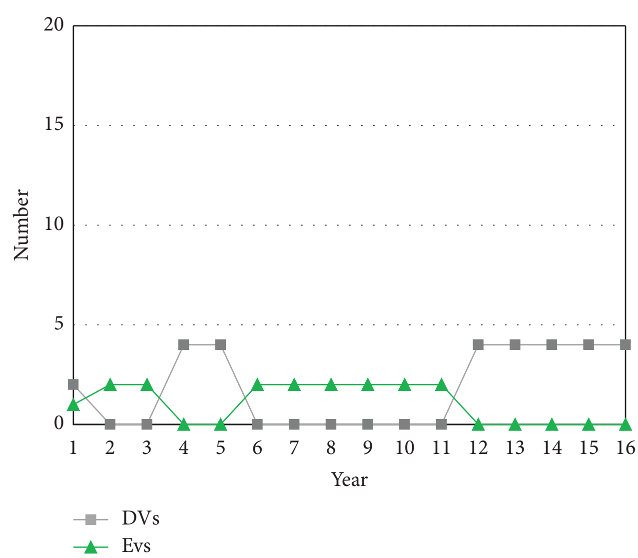

Figure 3: Number of purchased vehicles during the planning period.

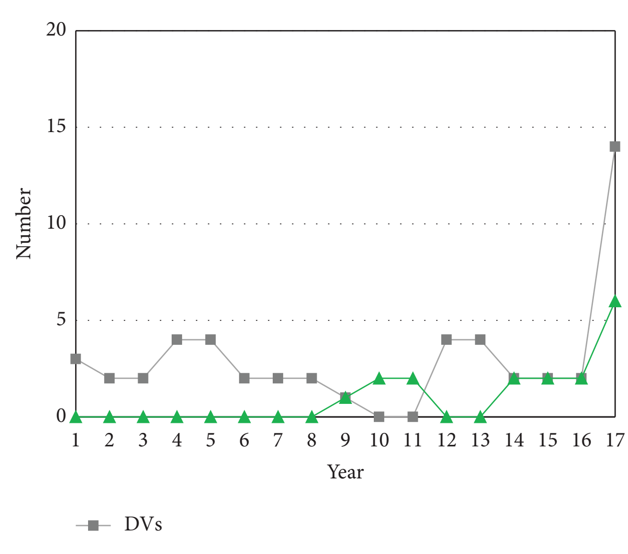

Figure 4: Number of salvaged vehicles during the planning period.

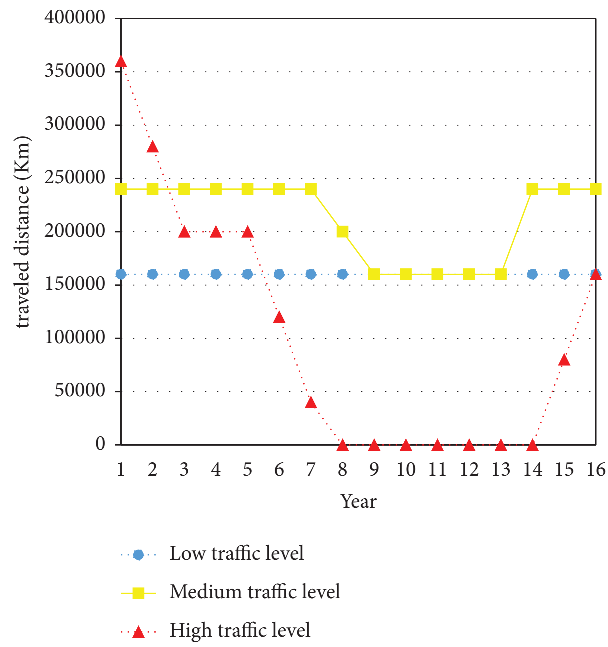

FIGURE 5: Traveled distance of diesel vehicles for different levels of traffic congestion.

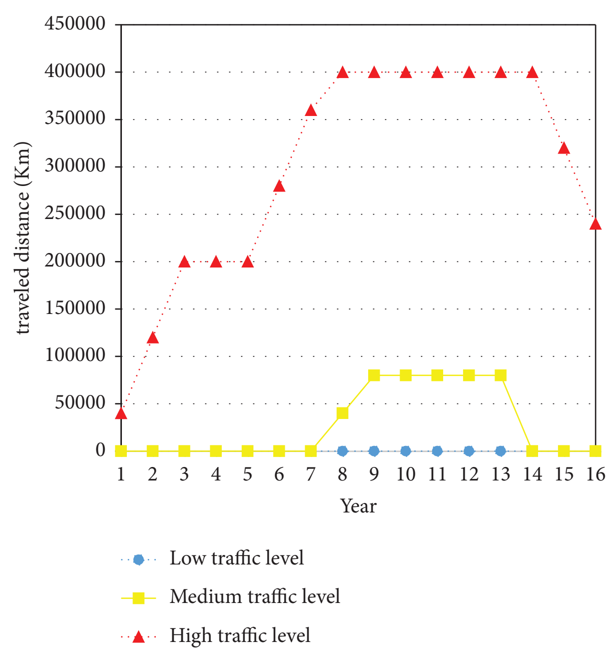

FIGURE 6: Traveled distance of electric vehicles for different levels of traffic congestion.

As we mentioned previously for this scenario, we consider the energy consumption of 0.062 lit/km and 0.145 kWh/km for DVs and EVs, respectively. This scenario led to an increase of 18% (from 1,955,629.032 to 2,310,844.077) in the total cost.

Table 4: Per-km discounted elasticity analysis of total cost for different factors.

Factor (range of values) (unit)	Baseline value	EA (TC, p)
Depreciation rate EVs (17–27) (%)	22%	0.012
Depreciation rate EVs (23–33) (%)	28%	0.053
Depreciation rate EVs (29–39) (%)	34%	0.068
DVs growth rate energy price (2.91–8.73) (%)	5.82%	0.256
EVs growth rate energy price (1.44–4.33) (%)	2.89%	0.018
Discount rate (3–7) (%)	5%	−0.180
EVs purchase price (25200–30800) (€)	28000 €	0.398
Energy price (1.044–1.275) (€/lit)	1.16 €/lit	0.351
Energy price (0.144–0.176) (€/kWh)	0.16 €/kWh	0.072
Emission cost (22.5–27.5) (€/ton)	25 €/ton	0.023
Lifetime (6–10) years	8 years	0.025
EVs maintenance cost (0.024–0.028) (€/km)	0.0260 €/km	0.037

5.1. Elasticity Analysis. As mentioned previously, there is a degree of uncertainty associated with some of the input parameters. Variations in these parameters can also impact the total cost. We performed an elasticity analysis on a number of key parameters to test their impacts on the total cost. To this end, we used the arc elasticity formula [57]as follows:

$$EA(TC, p) = \frac{\%chance\ in\ total\ \text{cost}}{\%change\ in\ parameter\ p} = \frac{\{p1 + p2\}}{\{TC1 + TC2\}} \times \frac{\{TC2 - TC1\}}{\{P2 - p1\}}, \tag{12}$$

where EA (TC, p) represents the discounted total cost (TC) per km in response to a change in parameter p.

Elasticity analysis was performed for different ranges of values to assist the operator in determining which parameter has the main impact on its optimal vehicle replacement decision. Regarding the deprecation rate of EVs, an elasticity analysis was performed for three different intervals. As expected, the purchase price of EVs, the energy prices related to the operation of DVs, and the growth rate in diesel prices have the highest impact on the total cost. The results of the elasticity analysis are presented in Table 4. A 1% change in one of these parameters leads to increases of 0.40%, 0.35%, and 0.26% in the total cost, respectively. For the discount rate range, the elasticity is negative, which means that when the discount rate increases by 1%, the total cost decreases by 0.18%.

6. Conclusions

Car-sharing can help resolve traffic congestion and emission issues arising from increasing mobility within urban areas. In comparison to diesel vehicles, EVs perform better in regard to energy consumption during peak-hour traffic congestion and low-speed flows. Taking this crucial factor into consideration, an optimization framework for introducing new vehicles of different types into the fleet of a car-sharing company over a certain planning period was presented. The developed framework considers the energy consumption and emissions of different types of vehicles at different levels of traffic congestion. To the best of our knowledge, this is the first time that such a framework has been presented for the optimal composition of the fleet of a car-sharing service. The numerical results showed that EVs, compared to DVs, become more competitive year after year during the planning period. The reason for the increase in the share of EVs is their low operating costs. More important, their competitiveness increases with the intensity of traffic congestion. Therefore, any decision made by a car-sharing operator that ignores traffic congestion intensity throughout the day as a factor would result in an onus, in the form of extra costs, for the company in question.

In this paper, an elasticity analysis is done to consider the uncertainty of input parameters such as the energy cost, maintenance cost, EV purchase price, and emission cost of different types of vehicles. In future work, it will be worthwhile to analyze the effect of these uncertainty parameters by using a portfolio theory approach such as the one developed by Ahani et al. [39]. We also assumed that the range limitation of EVs was not a determining factor for the purchase decision. Depending on the demand level for car-sharing services, there are some situations in which such an assumption seems unrealistic. Hence, another line of research could involve developing a vehicle replacement and assignment optimization framework by considering the range restriction of EVs and uncertainties associated with the network of available charging stations and demand for car-sharing service across an urban area. In this work, we did not take into account the charging station location, and no limitation was assumed with regard to the demand for charging EVs in a network of charging stations. However, in real scenarios, the network of charging stations might have a limited capacity for satisfying the uncertain demands for recharging the EVs. There are various research studies on finding optimal locations for refueling stations under different scenarios and conditions [58–64]. Therefore, from the standpoint of an urban decision-maker, the integration of the frameworks developed in the aforementioned studies into the optimization framework of the current research study will be another interesting future line of research.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Review Article

A Comprehensive Review on the Integration of Electric Vehicles for Sustainable Development

M. S. Hossain,[1] **Laveet Kumar**,[2] **M. M. Islam**,[3] **and Jeyraj Selvaraj**[4]

[1]*Institute for Energy Research, Jiangsu University, Zhenjiang, 212013, China*
[2]*Department of Mechanical Engineering, Mehran University of Engineering and Technology, Jamshoro, 76090 Sindh, Pakistan*
[3]*Department of Mechanical Engineering, Dhaka University of Engineering and Technology, Ghazipur, 1707, Bangladesh*
[4]*Higher Institution Centre of Excellence (HICoE), UM Power Energy Dedicated Advanced Centre (UMPEDAC), University of Malaya, 59990 Kuala Lumpur, Malaysia*

Correspondence should be addressed to M. M. Islam; moinul.islam@duet.ac.bd

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In this article, the concept of an electric vehicle (EV) as a sustainable development (SD) is discussed, and the viability of the development of electric vehicles is assessed. This study broadens the conventional definition of sustainable development by incorporating and prioritizing crucial areas of technology, environment, and policy performance. The proposed review studies have summarized the elements that can promote the integration of electric vehicle technology. The innovation of the EV has just become a modern innovation. At the same time, some obstacles, such as policy and lower adoption, are resisting its goals. To overcome this situation, electric cars have to adopt some innovative approaches that can be another path to success. The review result shows that the proposal discusses the technological advancements of electric vehicles worldwide and paves the way for further improvements. The results also mentioned technological development to reduce emissions and help us understand the impact on the environment and health benefits. However, the summary would be advantageous to both scholars and policymakers, as there is a lack of integrative reviews that assess the global demand and development of EVs simultaneously and collectively. This review would provide insight for investors and policymakers to envisage electric mobility.

1. Introduction

Electric vehicles (EVs) have the potential to contribute to the decarbonization of transportation and the emergence of low-carbon cities due to the benefits of energy-efficient technology and low pollution. Thus, it has become one of the development trends of interest in the automotive industry [1, 2]. However, the EV industry's future success is highly reliant on technological innovation [3, 4]. Many countries, including Sweden, China, Malaysia, and Korea, have paid close attention to EV technology innovation and issued policies to encourage EV technological innovation [5–8]. Nowadays, technological innovation in the electric vehicle field of sustainable development is a significant topic.

The most important reason is that, at present, environmental issues are becoming increasingly serious. Vehicle exhaust gas emissions have become the most significant source of air pollution, particularly in densely populated areas. In order to overcome the environmental and energy crisis issues that conventional vehicles contribute to, hybrid electric vehicle (HEV) technology has been developed and applied over the past few years. HEV technologies provide a fuel economy improvement and enable HEVs to exhaust fewer emissions compared to conventional internal combustion engine vehicles (ICEVs), but HEVs cannot completely resolve the abovementioned issues. Thus, vehicle technology has improved to produce pure electric vehicles (PEVs). As a result, PEV technology could reduce greenhouse gas (GHG) emissions and particulate matter ($PM_{2.5}$) air pollution as the world is suffering from dangerously high levels and poses a major environmental risk to human health [9]. Many studies have been conducted to reduce GHG emissions from vehicles. Without GHG standards, global CO_2 emissions from passenger vehicles would nearly double between 2000 and 2030 [10].

However, if current GHG standards are followed, global GHG emissions from passenger vehicles are expected to be slightly lower in 2030 than they were in 2000. Based on other research, currently implemented vehicle GHG emission standards will reduce 1.7 billion tons of CO_2 emissions from light duty vehicles (LDVs) in 2040, whereas CO_2 emissions from LDVs will be 5 billion tons in 2040 if GHG emission standards are not implemented [11]. Sen et al. have estimated the impact of GHG standards on the market share of electric vehicles (EV) because zero-emission vehicles are more likely to meet GHG standards, also known as the corporate average fuel economy (CAFE) [12].

The researchers from different countries used various methods to assess the environmental impact of EVs. Many researchers have discovered that electric vehicles (EVs) can help to reduce GHG emissions in a variety of ways [13–15]. For example, Hawkins et al. discovered that in Europe, EVs could offer a 10% to 24% reduction in global warming potential when compared to conventional diesel vehicles [16]. According to Onat et al., all-electric vehicle types could help to reduce global warming in Qatar [17]. Some scholars believe that electric vehicles may not help to reduce greenhouse gas emissions [18–20]. Some researchers deny the actual environmental benefits of EVs, owing to a lack of EV stock and the power utilized by EVs being insufficiently clean. For example, more than 70% of China's electric power is generated by burning coal or natural gas. The power production industry is well-known as a source of air pollutant emissions, including sulfur dioxide (SO_2) and nitrogen oxide (NO_X) emissions [21]. The source of electricity generation emits a large amount of greenhouse gases, which makes the popularity of EVs appear to be environmentally unfriendly [20, 22–24]. The electric vehicle contributes to global warming mitigation if the electricity generation system is powered by renewable and sustainable energy [25–27]. However, Khan et al. have discovered a comprehensive study on solar-powered electric vehicle charging systems [28]. As a result, from an environmental viewpoint, EVs remain a promising trend for decarbonizing transportation and can contribute to sustainable development [29].

The sustainable development framework is the most important model or framework to consider when developing new technology. Such frameworks take into account various aspects of development, such as social, economic, environmental, and technological factors. Furthermore, the development of international standards and codes, universal infrastructures, associated peripherals, and user-friendly software will be critical to the successful growth of EVs over the next decade [30]. Huge teams of researchers are working in these fields all over the world. Khalid et al. and their research team have enclosed a comprehensive review on advanced charging topologies and methodologies for electric vehicle batteries [31]. They focused on EV charging technologies regarding charging methods, control strategies, and power levels. Ahmad et al. developed an existing EV charging infrastructure and energy management system for smart microgrids [32]. The charging infrastructure of electric vehicles relays on the grid system, thus unscheduled EV connectivity with conventional grid systems leads to unreliable and interrupted power supply, which may lead to grid failure. Therefore, the smart city development and energy management systems could respond to the smart grid system, which includes renewable energy sources (RESs) and EVs, respectively. That research shows a good summary of the progress of EV charging infrastructure and the impact of EV charging on the grid, which, on the other hand, is critical for the growth of the EV market. However, several authors summarized EV charging infrastructure [33–35], EV integration into the smart grid [36], vehicle-to-grid (V2G) technology impact [37], battery swapping stations for electric vehicles [38], and EV and smart grid interaction [39] in various publications. But taking part in single approaches may not be suitable for EV adoption growth. There are several supporting strategies, such as environmental and health impact, policies to help EV technology improvement, and sustainable development worldwide.

To improve EV adoption growth towards sustainable improvement, this paper proposes an innovative approach for EV development to provide an important guideline with examples for developing and nondeveloping countries. Such approaches consider various aspects of development, such as technical, environmental, health, and policy. The study is summarized from the standpoint of sustainable development using electric vehicle technology and its impacts in different sectors. The technological development could not help to increase EV adoption. Thus, this review points to the technological improvement rates including such key dimensions as human, nature, and system factors. EV technology with future smart city development is the key factor for renewable energy system development, which could help to reduce the impact of EV integration on the grid. The smart grid structure with EV system impact has been discussed in this review. The following article summarizes EV policy, which is a significant contribution to recognizing the major improvements in EV use in different countries and necessary methods. The review summarized the EV adoption hypothesis, which could improve the sociodemographic and psychological characteristics. Nowadays, EV sharing and its benefits are hot topics, and electric vehicles are playing an essential role in environmental and infrastructure benefits. In this regard, the review went through the vehicle sharing mobility structure discussion. Lastly, the paper summarizes and explores some different methods and their advantages and disadvantages, which could continue the development of electric vehicle innovations with a sustainable energy management system. These discussions will give a general framework for increasing EV growth in the world.

The structure of this article is as follows: in the next section, we summarized the electric vehicle technology development approaches. Section 3 summarizes the CO_2 emission and reduction approaches with different countries' alternative fuel vehicle studies. Sections 4 and 5 show the EV's environmental and health impacts. Section 6 summarizes the electric vehicle policies and major improvements for EV development. Section 7 outlines the advantages and disadvantages of electric vehicles. In the last section, the study covers the conclusion and makes a recommendation.

2. Electric Vehicle Technology

Currently, the world is facing atmospheric changes and emissions of ozone-depleting substances [40, 41]. Most of the conventional vehicles carry substances that deplete the ozone layer. According to a declaration issued by the European Commission, transportation sector is responsible for a quarter of the total ozone layer depletion in the European Union (EU). One of the main ozone-depleting materials is CO_2 gas, and about 15% of CO_2 is emitted by light vehicles [42]. The revolution of electric vehicles has stirred up great interest from analysts, governments, and strategic designers in many countries. Today's electric vehicle (EV) technology stems from various types of individual achievements that divides the overall field of EV into several key areas [43]. Because of their low pollution level, EVs can promote low-carbon emission and present a model for decarbonization of transportation in automobile sector [1, 2, 44]. Nevertheless, future expansion of EVs depends on technological improvement to a great extent [3, 4]. Policymakers in many countries like Sweden, China, Malaysia, and South Korea are serious about developing strategies to support the new inventions in this field [5, 45].

Figure 1 shows the analysis of the estimated improvement index the estimation steps to improve the areas and subdomains, where PE is the hardware and EM is the electric motor.

There are various analytical models to appreciate the sustainable and unsustainable development of electric vehicles. An enhanced version of the HNS model (human, system, and nature) has been developed for mechanical steering of EV, which is then converted into NHS to show versatility from N to H and then converted to H to S. An idea of the relationship between people, nature, and systems is shown in Figure 2. As shown in Figure 2, each of the three representations is adjusted equally in accordance with their proposed model (NHS)—case (a) is more supportable than (b), and (b) is more practical and therefore better than case (c). In the proposed model, nature, human, and systems are considered independently (Figure 2), whereas humans depend on nature and nature will remain without people, and the structure depends on both humans and nature. As a rule, support infers a rational approach to limit negative environmental impacts trying to maintain harmony between all three components. The opinions of people and structures are discerned from a natural viewpoint [46].

There are three types of electric vehicles: hybrid electric vehicle (HEV), fuel cell electric vehicle (FCEV), and electric vehicle (EV). According to [47], all PHEVs in a municipal fleet can be divided into the following six categories, where vehicles in category 2 are modular electric vehicles that are operated by, at least, one electric motor using the energy stored in batteries.

(1) Electric bicycles and bicycles

(2) Street electric cars

(3) High-speed urban electric vehicles

(4) Low-speed electric cars

(5) Supercars

(6) Electric bus and electric truck

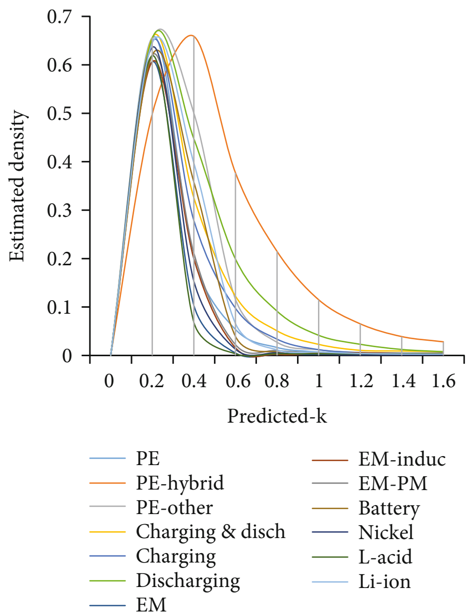
A model for relationship between EV and the grid is shown in Figure 3 [41, 48]. To overcome the low-voltage and high-load systems, it is recommended to connect or charge EVs to the grid at a specific time. However, EV technology advancement may not only increase EV adoption. There are several criteria needed for energy management methods and policies to give motivation to EV customers. A study using bilevel mathematical model to capture the decision-making processes of the transport agency and the travelers can serve as guidance for metropolitan transport agencies to establish specific locations and capacities for EV [49].

2.1. Flexible and Innovative System in the Vehicle. In near future, dynamic mobility between fully electric vehicles (EVs) and plug-in hybrid electric vehicle (PHEV)) will become an imperative choice for the smart grid area [50]. Hence, an energy management mechanism is desirable to endorse the link between household business taxes and fast car charging. One of the best choices required for flexible and unique utilities is EV [41, 51], the function and focus of which include strategy to ensure high response speed and transfer energy in two directions.

2.2. Future Development Model of Electric Vehicle Network (EVGI). Electric vehicles can be used not only as transportation but also as electrical loads (grid to vehicle (G2V)), the corresponding energy stock of grid (vehicle to grid (V2G)), the energy stock of various electric vehicles (vehicle to vehicle (V2V)), and the energy stock of buildings (vehicle to building (V2B)) functions system compliance center [52, 53]. In the field of vehicles, some of the latest innovations include proprietary long-distance power transmission (wireless power transfer (WPT)) [54], connected mobility (CM), autonomous or autonomous electric vehicles, and the economic saving and life power network of electric vehicles. Figure 4 shows a classification, and Figure 5 shows a recommended model for the future development of EVs and energy structures. This proposed structure includes renewable electricity and hydrogen generation for battery and fuel cell EVs. On the other hand, energy networking systems have been developed for energy utility, distribution, and transmission control systems, whereas EV is contributing as a utility and energy distributer.

2.3. Application of Renewable Energy. This section studies the impact of renewable energy systems in implementing EV. Knezović et al. [55] studied the opportunity and exertion of synchronizing sustainable energy sources (for example, based on wind and sun) to provide energy for battery charging and limiting greenhouse gas (GHG) emissions. PEV can charge electric vehicles in peak-off hour or when the renewable energy is available. There is a lack of coordination between the host and the distributed generation energy system (DESS) with sustainable energy, which can be completed under the basic load and the maximum load. At the top time, supplementary energy is fed into the grid. From the literature, we found that primarily, the broader prospects of entire future grid system and network have been studied so far [41].

2.4. Smart Grid Structure. Smart grid is a multifaceted system connected to all grid networks. At present, the power grid network does not meet the flexibility required to facilitate EV



Domain & subdomain	Improvement (%)
PE	18.3
PE-hybrid	38.5
PE-other	15.8
EM	7.7
EM-PM	10.1
EM-Induction	9.4
Charging & dis	23.8
Discharging	28.6
Charging	21.9
Battery	11.7
Battery-lithium-ion	13.2
Battery-nickel	8.7
Battery-lead acid	5.1

Figure 1: The estimated technological improvement rates of domains and subdomains [43].

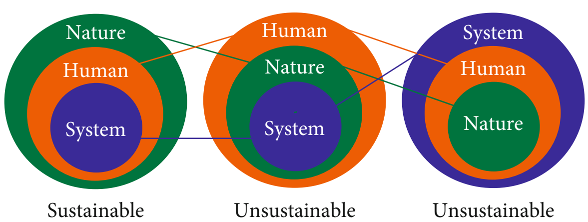


Figure 2: Models for human, structures, and nature (HNS): (a) sustainable and (b and c) unsustainable. Redrawn from this source [46].

charging. For the exhibition of all system screen characters for this application, various networks need to be effectually cliched, connected, and permitted. The following are the main components of planning a keen system [41, 52]:

(1) The substructure of the system and its components must be adaptable

(2) The structured grid model should support future growth

(3) When planning the structure, the structure and points of the programming/device/grid structures should be considered

(4) Any system update program should be executed automatically

2.5. Impacts of EV Integration on the Grid. However, this section's information is important to observe the impacts of EV integration on the grid. We summarized the effects of mixing the EV grid, which can be divided into negative and positive. It is recommended that before connecting EV technology to the grid network, there will be significant heavy load problems. However, EV technology still needs to be synchronized to the national grid system. A short details are shown in Figure 6 [52].

2.5.1. Negative Effects. Electric cars are a wonderful test for energy suppliers. The unnecessary integration of electric vehicles into a decentralized system can affect the shape of the stack, the limits of the components of the transport frame, tension and repetitive accidents, injection of upper symphonies, a power failure, and financing stability.

2.5.2. Positive Effects. Although top-level EV access to the network can cause problems such as damage to the quality of the degradation, increasing maximum loads, and power recommendations, each of these problems can be resolved using executive power techniques, such as [37, 56, 57].

2.6. Approach Time to Charge the Battery to Reduce Negative Impacts. Synchronous loading is one of the most effective strategies. The transaction costs for energy, a measure of the energy consumption of a battery in the state of charge (SOC) (Figure 7(a)), are regarded as the parameters of this technology. In the independent state of charging, 55% of the battery charge is accomplished, and additionally, 45% is supplied during low use (10:00 p.m. to 7:00 a.m.). In express delivery, 75% of the EV battery charge ends when used less (10:00 p.m. to 7:00 a.m.), and the remaining 25% is made available between 7:00 a.m. and 10:00 p.m. In an uncontrolled state of charge, 55% of the charging time of the battery is used during periods of low usage (10:00 p.m. to 7:00 a.m.), and the remaining 45% is between 7:00 a.m. and 10:00 p.m. [12].

A proposed charging schedule is shown in Figures 7(b) and 7(c). One of the primary difficulties with this strategy is that during periods of maximum energy consumption,

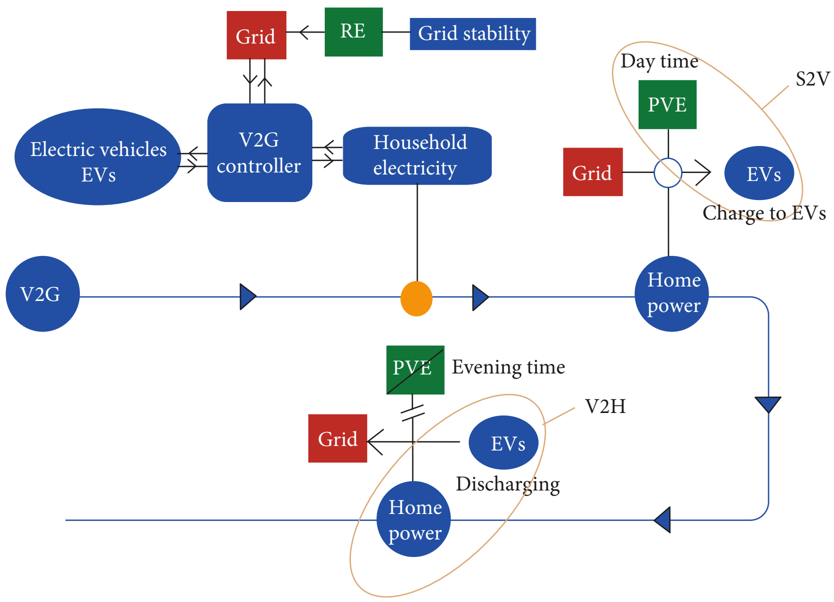


Figure 3: The relationship between electric vehicles and the grid.

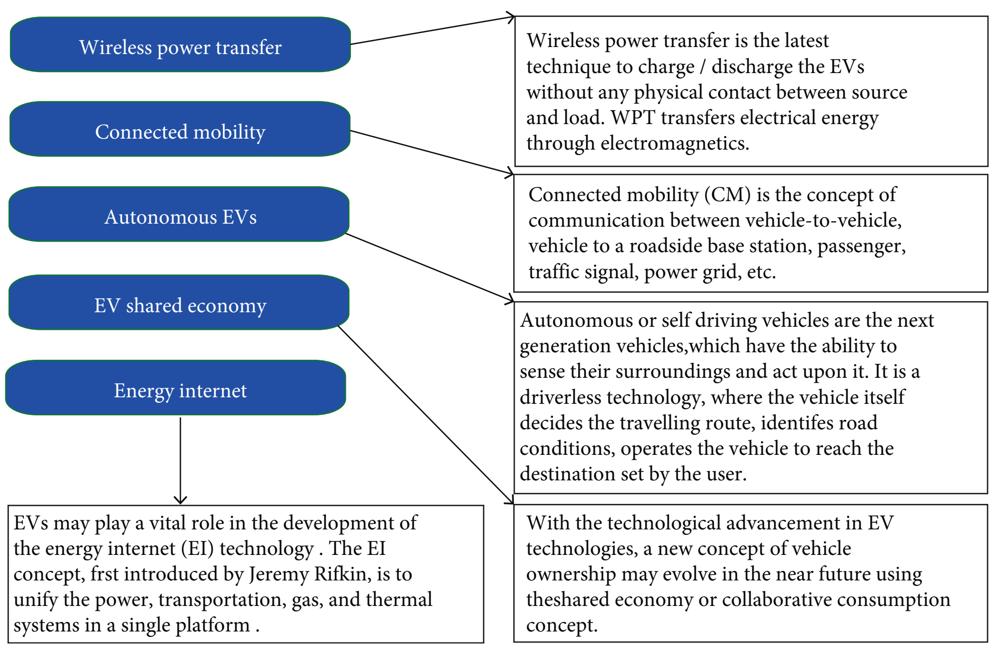


Figure 4: Classification of EV network.

the charging of connected EVs gets restricted. The following mode (controlled state of charge) is considered.

The updated lithium battery is suitable for charging EVs with a range of 170 kilometers. The maximum battery charge of EVs is around 20 to 30 kWh. EV FC batteries can charge 80% of EVs in less than 30 minutes.

3. CO_2 Emission and Reduction Approaches

Apart from the positive impact, we believe that EVs could be a suitable technological option for renewable energy sources. However, for sustainable development, EVs could contribute to the environmental impact. Synchronization between issues related to global temperature change and air pollution are vital for a cleaner transportation sector. The International Energy Agency (IEA) is taking measures to reduce carbon dioxide (CO_{2eq}), and many countries have adopted the introduction of EVs in the market as an important policy [59, 60].

Many observations focused on the development of electric vehicle advertisements in various departments and countries, such as in the United States, Iceland, Canada, and the Netherlands [61–64]. From 2012 to 2013, the development of cooperation between electric vehicles in the Scandinavian market was determined by measuring the possibility of using various forms

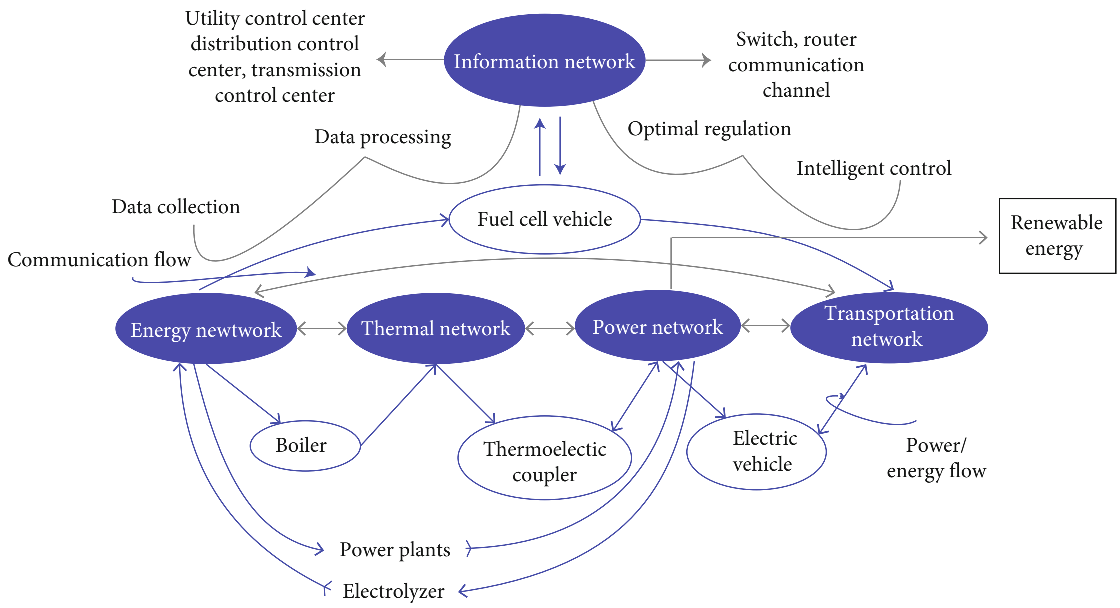


Figure 5: Structure of energy network. Redrawn from this source [52].

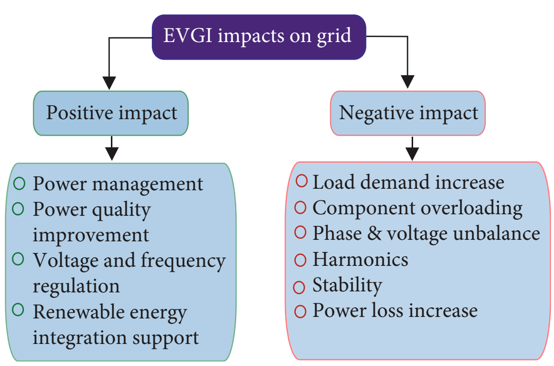


Figure 6: Negative and positive impacts of EV grid integration system. Redrawn from this source [52].

of financing to purchase electric vehicles [61]. The outcomes indicate that the decisive factors are the development of fuel and electric vehicle costs and the driving force behind the government. Many tests use virtual models to estimate the cost of emissions from electric vehicles. Therefore, further research on real information about electric vehicles is required [65]. Buyers of electric vehicles are required to use their local grid discharge as a guide for EV statistic, which is a dangerous deviation from atmospheric deviation due to different radiant forces in the area. Appropriate models for determining the age limit of electricity consumption and carbon dioxide emissions for electric vehicles take into account the explicit radiation factor of the energy service life, which is why it should be carried out on site [66].

As people pay more attention to environmental changes, more attention is being paid to reducing carbon dioxide emissions than ever before. Carbon dioxide from the automotive industry, in particular, accounts for 22.9% of global emissions [67]. More than 190 countries have created plans to carry out the exercises foreseen after 2020 as part of the Intended Nationally Determined Contribution (INDC) [68]. South Korea proposes to reduce the runoff of greenhouse gases (GHG) by 37% by 2030 as an INDC. They believe that this will be achieved by reducing carbon dioxide emissions in the family car sector by 30.8 million tons in terms of carbon dioxide, which equates to the target emission reduction of 11.1% [69]. In order to reduce greenhouse gas emissions from the automotive sector, the Korean government has reached an agreement to create and provide institutional assistance to the global green automotive industry [70]. Electric vehicles (EVs) and fuel cell electric vehicles (FCEVs) play an important role, especially in response to environmental concerns and future interest in cars. In light of these environmental and economic considerations, the Korean government has set targets for the elimination of electric vehicles and FCEVs and is looking for various methods of assistance [71, 72].

3.1. Different Country's Strategies for Alternative Fuel Vehicles (AFVs). Figure 8 shows different countries' strategies for alternative fuel vehicles (AFVs). We summarized the important studies and methodologies for AFVs' performance and contribution to reducing GHG emissions. Previous alternative fuel vehicle (AFV) surveys show that customer preferences for fuel type vary by country/region and inspection time. In addition, in many studies, the probability of making an AFV decision is less than that of an internal combustion engine. Especially considering the opening and charging time of the charging station and taking into account the various characteristics of various studies, with the current level of innovation, internal combustion engine vehicles (ICEV) are even better than AFV [72], but ICEVs produce more GHG emissions than AFV. However, based on environmental and health benefits, AFVs such as BEV and FCV technology could provide an alternative means for sustainable development. The problem of locating refueling stations in a transportation network via

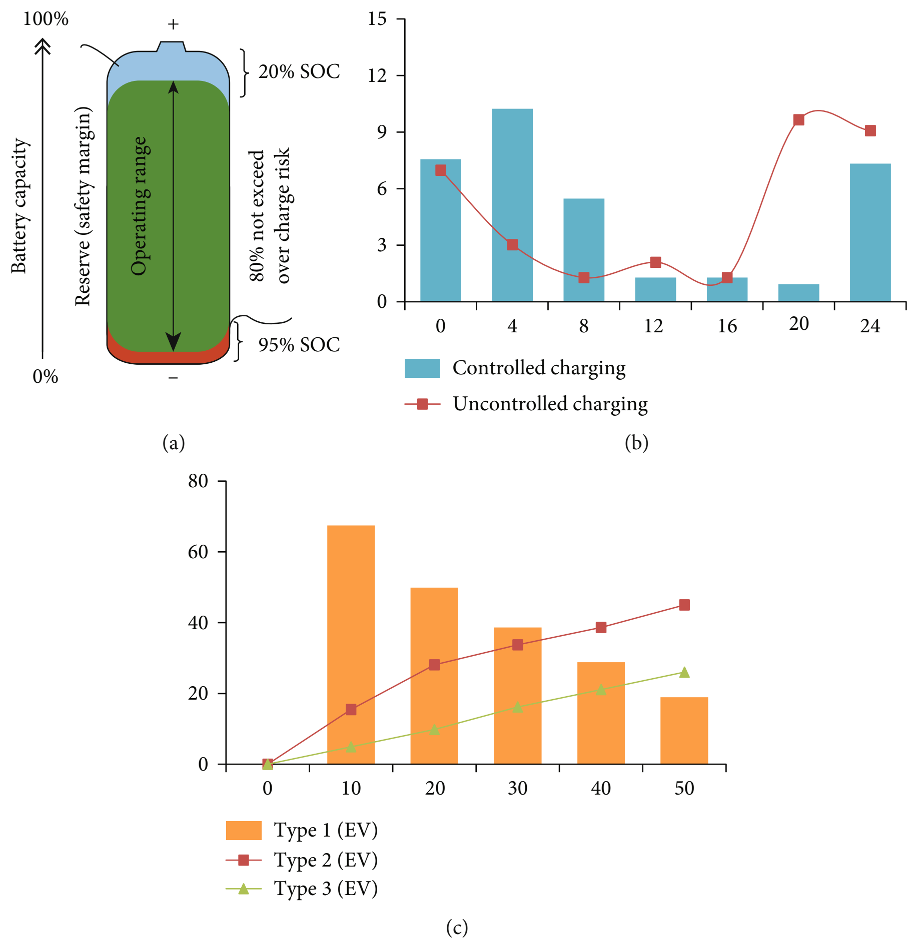


FIGURE 7: Charging schedule of EVs. Redrawn from this source [58]. (a) EV battery capacity. (b) Charging is limited during peak times. (c) Charging process is completed before 6 a.m.

mathematical programming has been carried out by [73]. The proposed model is applicable for several alternative fuel types and is particularly suitable for hydrogen fuel.

Various studies have shown that a clear energy structure in the United States is a key factor in AFV greenhouse gas emissions. To reduce the reduction of medium- and long-term AFV greenhouse gas emissions, some AFV assumptions need to be considered, as well as customer trends and mechanical innovations, as well as state regulatory mechanisms for energy consumption. It is recommended that we follow the different countries' AFV methodology to overcome the EV performance issues and use those technologies for sustainable development. Based on the life cycle assessments around the world, AFVs perform better than ICEVs. For example, in the European power mix, EVs can reduce GHG emissions by 10 to 20% compared to ICEVs. On the other hand, GHG emissions from hydrogen production are analyzed in the context of South Korea. They used well-to-wheel (WTW) approaches to reduce GHG emissions. However, since a large portion of the power sources around the world are fossil fuel based, EVs may not be effective in reducing GHG emissions. Thus, EV technology needs further improvement (i.e., fuel cell technology) and policy implications to achieve deep decarbonization from power to transportation sectors. In the following section, we provide some research and future prediction outcomes for EV development in the road transportation sector in South Korea and China.

3.2. CO_2 Emission and Reduction Scenario Approaches. This is a proposed assessment of carbon dioxide emissions and approaches of reducing the use of heavy-duty trucks under various conditions of emission acceptability in South Korean. Mechanically achievable carbon reduction levels apply to the following four situations: similar to business as usual (BAU), mild, normal, and aggressive conditions. In the estimation of CO_2 emissions, a simulation model based on the longitudinal component of the vehicle, the normal vehicle mileage, and the number of Korean vehicles has been used, as shown in Figure 9. According to BAU, 30.82 million tons of carbon dioxide will be produced by 2030 and carbon dioxide emissions will be cautious and sensitive and, as a rule, will decrease by 2.1%, 4%, and 5%, respectively. By 2040, the impact of these conditions will be reduced by 5.7%, 10.9%, and 15.8%, respectively. These results indicate that South Korea can reduce CO_2 emissions through strict improvement measures or CO_2 regulations for vehicles [74].

Here is another example. China is by far the best private electric car advertisement in the world and flexibly represents

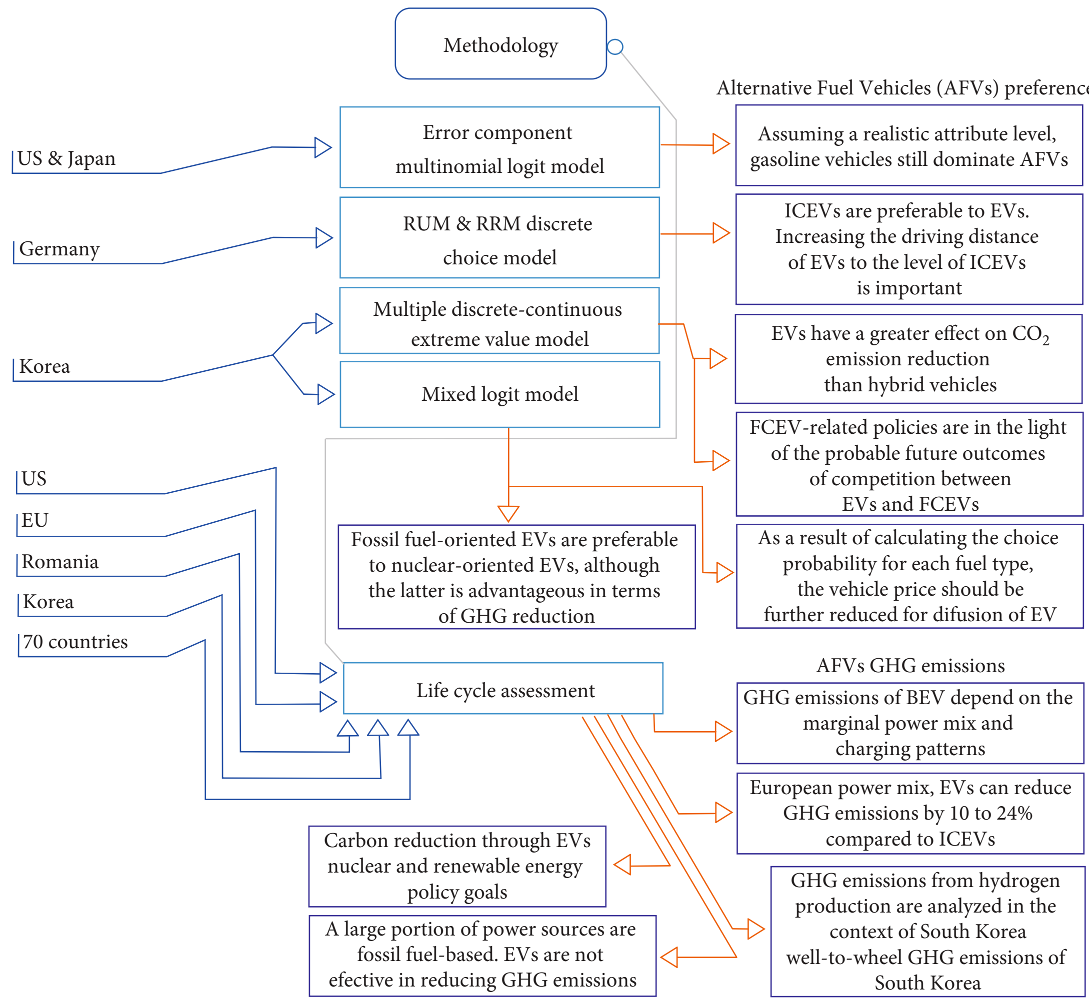


Figure 8: Summary of the relevant studies.

part of the world's private car in 2017. The China data research center of Automotive Technology & Research Center has maintained an extensive database of prices and quality. This data can be used to evaluate the environmental impact of the PEV in China [75].

Always indicate eVKT (vehicle kilometers travelled) of BEV and PHEV in 5 districts. From 2011 to 2017, BEV covered 12.5 billion kilometers in 5 regions. Beijing invested over 30% in all electronic quotas; Zhejiang, Guangdong, and Shandong accounted for around 20%; in Tianjin, it is less than 10%. From 2011 to 2017, 5.8 billion kilometers were spent in 5 regions. Shanghai represents 55% of the PHEV recommendations, Guangdong 32%, and less than 5% in the other three regions. Between 2011 and 2017, these five districts spanned a total of 1.83 billion kilometers. In 2017, PEVs accounted for 70.1% of the 9.7 billion kilometers guaranteed by battery-based EVs.

Figure 10 shows the absolute annual CO2R for BEV and PHEV, respectively. From 2011 to 2017, BEV carbon dioxide outflows in Beijing and Zhejiang declined. In any case, from 2011 to 2013, BEV went to Guangdong, from 2014 to Shandong and from 2012 to Tianjin, carbon emissions have increased, and the ICEV has also been limited. Although carbon emissions in Shandong and Tianjin are generally high, this increase in runoff is due to the generally low natural impact of destroyed vehicles in Guangdong.

In Shanghai, from 2011 to 2017, the outflow of carbon dioxide from PHEV continued to decline. Between 2011 and 2017, plug-in hybrid cars have grown steadily in Guangdong, Tianjin, and Shaanxi in the past 4 years (except 2016) and in 2017. It is unclear whether PHEV-CO_2 in region 5 has completely run out until 2015. The model is also explained by the general environmental impact of top models such as Guangdong, Tianjin, and Shaanxi, although the CO_2 emissions in Tianjin and Shaanxi are slightly higher. In 2017, the PEV produced 355,827 tons of carbon dioxide in five main locations. About 80% of this volume is provided by BEV and 20% by PHEV. In 2017, each BEV model emitted 606.6 kg of carbon dioxide, and each PHEV model emitted 350.9 kg of carbon dioxide. Although BEV and PHEV disposed of 472,806 tons and 139,018 tons of carbon dioxide from 2011 to 2017, respectively, the PEVs generally reduced 611,824 tons of carbon dioxide [76].

The above results show the performance of EVs and EV-related policy applications. That progress mainly depends on a country's policy and identifying the best technology to fit

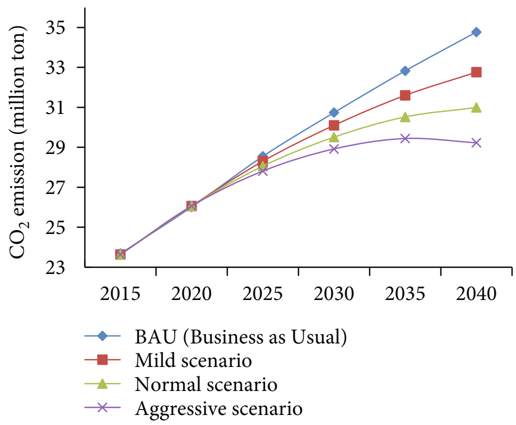


Figure 9: CO_2 emission reduction in South Korea [74].

into the market. However, underdeveloped countries should learn from EV growth countries' experience. A good EV policy could help to reduce GHG emissions and environmental and health impacts from the transportation sector. To support this powertrain electrification, China and India launched subnational level policies to inspire electric vehicle demand, local manufacturing, research and development (R&D), and infrastructure development. Therefore, technology and policy have a significant role in EV growth and adoption.

4. EV Environmental Impact

Since the introduction of the most advanced combustion engine in 1885, transportation has only been achieved through fossil-fueled vehicles. Today, vehicles account for 29% of global carbon dioxide emissions, while individual vehicles account for 10% [77]. In addition, by 2025, less than 5% of vehicles in the United States will correspond to corporate average fuel economy (CAFE) [78]. On the other hand, EU regulations stipulate that by 2020, the bound emissions of carbon dioxide must reach 95 g/km, which means that more than 95% of cars still do not agree with the standard [79]. As a result, the main contest is the amount of adoption for EVs versus clean electricity fueled. In 2009, a fascinating study was conducted, showing the advantages of PHEV and HEV vehicles in achieving emission targets and reducing fuel consumption compared to regular vehicles [80]. At this point, the restriction that restricts the use of electric vehicles as a standard rather than an exception seems to support hybrid electric vehicles. However, the environmental impact of HEV largely depends on its internal combustion engine "range extender" [81].

Another major disadvantage of simple fractional alternatives is that, despite many other options, they all produce nearby toxins such as some CO, NO_x, and PM. Contrary to the flow of carbon dioxide, these particles have local characteristics that affect air quality within 100 km [82]. Several sources indicate that this reduction in carbon dioxide emissions can reach 100%, while SO_x can be reduced by 75%, NO_x can be reduced by 69%, and PM_{10} can be reduced by 31% [83, 84]. In this regard, urban areas are exposed to another type of pollution: noise pollution. In all respects, a quiet EV can reduce the noise level by 3-5 dB (A) [85]. Nonetheless, some experts found this reduction to be a conflict advantage, especially due to helpless street customers [86], and emphasized the need for additional security measures.

The location of countless electric vehicles poses environmental problems associated with battery disassembly. Although it is currently impractical to use lithium batteries incompletely, lithium batteries contain hazardous components inherent in the toxicity of electronic equipment and must be properly disposed of. There are many reasons why lithium batteries are more difficult to predict and more expensive than lead-acid batteries. Initially, lithium batteries were equipped with a series of accessories, including $LiCoO_2$, $LiMn_2O_4$, $LiNiMnCoO_2$, $LiFePO_4$, $LiNiCoAlO_2$, and $Li4Ti5O_{12}$, which made the automatic reuse process difficult. In this case, the dynamic materials in the battery cells of Li particles are coated with metal foil powder, which needs to be separated during recycling. Lead-acid batteries are always made of a small number of large lead plates and are located in a single plastic case, but in most cases, many individual low-limit batteries and lithium particles are bundled in the module [87, 88].

4.1. Electric Vehicle Battery Recycling. From an environmental point of view, the rapid growth of the electric vehicle market will not cause a large number of lithium-ion batteries to expire. If they enter the recycling program or are improperly used, they will generate a lot of toxic waste. Stringer and Ma [89] found that due to the strengthening, the global electric vehicle load will reach 55,000 to 3.4 million from 2018 to 2025. These batteries are no longer suitable for electric vehicles. However, they have less than sufficient limits for certain fixed capacities (for example, storing energy on a private, modern, and basic scale). However, according to Nissan CEO Francisco Carranza [90], the price of EV battery materials that can be disposed of permanently is much lower than the price of fully used batteries. Since the used EV battery has enough energy to meet the less demanding tasks (such as RES energy storage), and since the use time can only be about 8–20 years [91], this will undoubtedly be reused again. This wise approach is called the second demonstration of using electric vehicle batteries, and some organizations have recommended it, for example, Nissan and Hyundai. Marra et al. [92] found that the ratings of batteries with potential for reuse are almost several times higher than the ratings of batteries that are increasingly suitable for recycling [93].

4.2. Electric Vehicle Effect on Electric Scaffolding. At the turn of the 20th century, global temperature changes and environmental pollution issues became the main issues of general legislative issues, which led people to seek the choice of petroleum products functionally and may revive electric vehicles. At the same time, the rapid expansion of the state-supplied electricity supply can benefit both the land and the real test of the energy structure. Huang et al. [94], described that the emergence of electric vehicles will cause a "top-down" impact, which may lead to serious risks related to the power system, for example, in southern Norway in 2017 [95]. These risks include an increase in the short-circuit currents; the voltage level could no longer be between the standard limits; the power demand is higher and the lifespan of the equipment is affected.

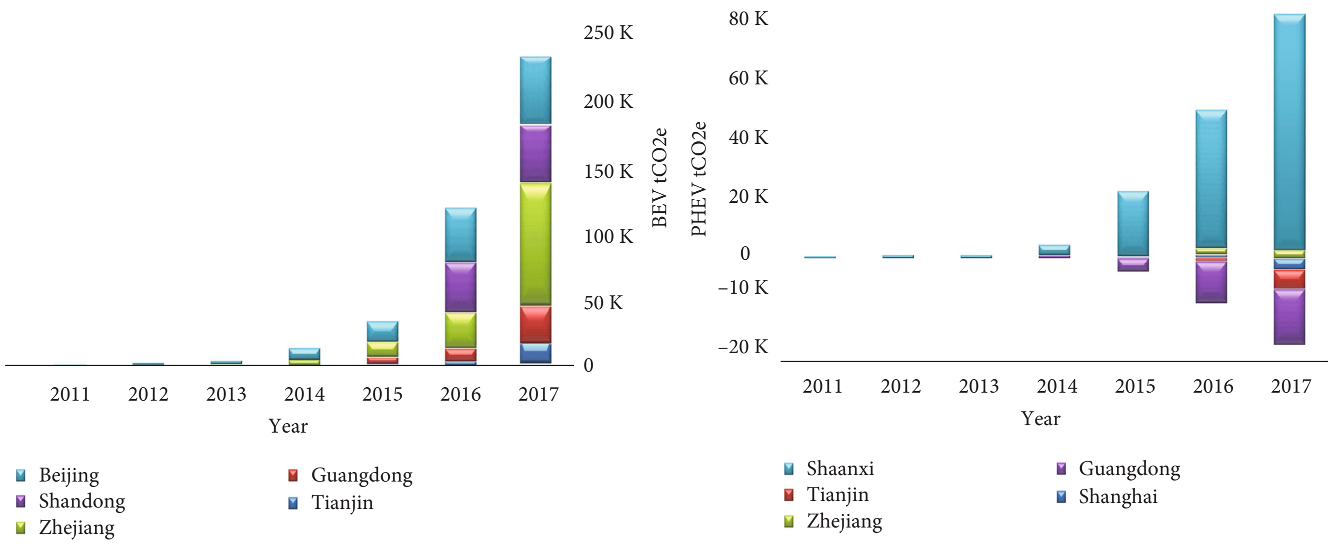


Figure 10: Top 5 BEV and PHEV CO_2 emission reduction in China [76].

However, the EV hosting capacity of the grid is good for a majority of the end-users, but the weakest power cable in the system will be overloaded at a 20% EV penetration level. The network tolerated an EV penetration of 50% with regard to the voltage levels at all end-users in Norway. Injecting reactive power at the location of an installed fast charger proved to significantly reduce the largest voltage deviations otherwise imposed by the charger [96]. Various scientists have raised comparable questions about these issues [97, 98].

5. Health Impact

Vehicle-driven innovations such as electric vehicles (EV), including hybrid electric vehicles (HEV), plug-in HEV (PHEV), and battery electric vehicles (BEV) have potential economic, environmental, and health benefits, but they need to recognize the impressive benefits of open EV reception. Anyway, in the United States, only a small percentage of electric vehicles need to investigate the behavior of the vehicle distribution in order to identify the current consumers of electric vehicles based on the attributes and settings of the electric vehicle while also considering competitive solutions, which are assembled fuel and diesel ordinary vehicles [99].

EVs powered by low-emitting electricity from natural gas, wind, water, or solar power can reduce environmental health impacts by 50% or more compared of ICEVs [100]. Considering the age of sustainable energy use, German electric vehicle emissions are 62-64% lower than traditional vehicles [65]. However, many scholars believe that the promotion of EVs in China cannot achieve energy savings or greenhouse gas reduction in most provinces due to their power structure [101]. Certain environmental benefits can only be realized in certain well-established or low-carbon regions [102]. Increasing the proportion of renewable energy, such as hydropower, wind, and solar power, in the power supply system can effectively reduce the negative environmental effects of EVs [27].

5.1. Well-to-Wheel Approach. The well-to-wheel analysis is a nonstandardized method to quantify the impact of transportation fuels and vehicles regarding energy and climate change. According to the life cycle concept, the US Department of Energy's Argonne National Laboratory has proposed a well-to-wheel (WTW) rating system for studying vehicle fuel consumption. Well-to-wheel is the first step in comparing the efficiency of different solutions towards greenhouse gas (GHG) emissions. Those GHG emissions are so crucial to mitigate because, simply put, they cause climate change. The subject of the assessment is the support of the vehicle's fuel base, which is divided into two stages: the level of fuel production (or from the well-to-tank, WTT) and the ignition level of the fuel (or from the fuel tank-to-wheel, TTW). The former includes the extraction, transportation, and conversion of fuel. The WTW method focuses on the life cycle of fuel consumed by the vehicles without describing the vehicle manufacture, scrapping, and recycling. Figure 11 shows the system boundary of the well-to-wheel approach structure [20].

Figure 12 shows an example of the EU energy mix in the transportation sector. Let us compare vehicles that are powered by gasoline, diesel, plug-in hybrid electric vehicles (PHEV), batteries, and compressed natural gas (CNG) [103].

There are some immediate assumptions from this simple example:

(i) On a TTW basis, electrified solutions offer the best performance. These are the emissions coming directly from the vehicle

(ii) Considering the current EU energy mix (106 g CO_2/MJ), the WTT CO_2 contribution from BEV is approximately double compared to conventional fuels. These are the emissions coming from the fuel or, in the case of electric vehicles, the electricity production

(iii) On a WTW basis, BEVs offer better performance thanks to the better efficiency of the powertrain

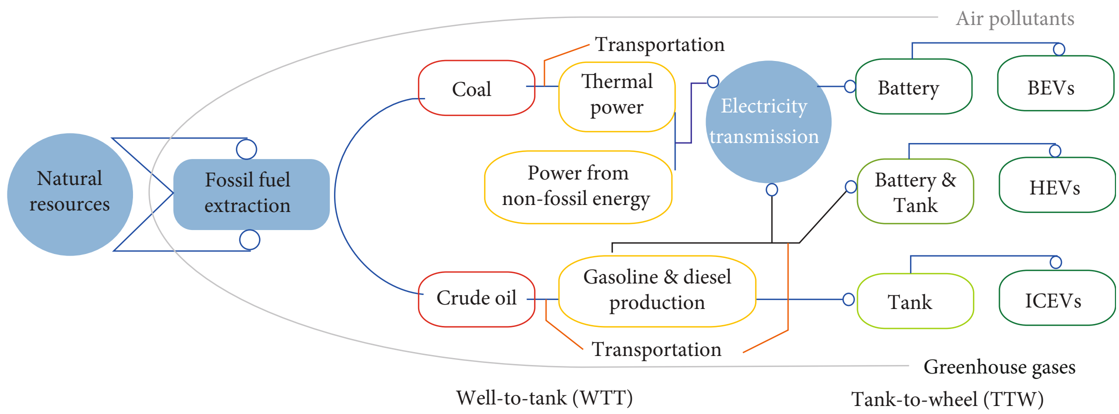


FIGURE 11: Well-to-wheel system bounder [20].

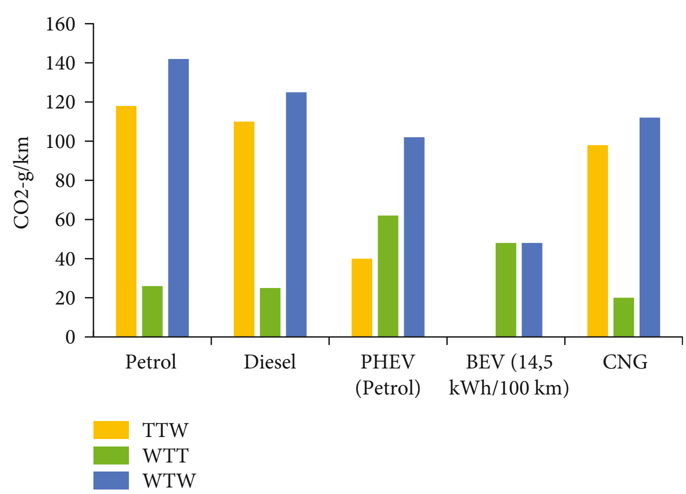


FIGURE 12: WTW emission comparison C-segment vehicle—WLTP [103].

5.2. EV and Health. Despite continuous innovation and improvement, the automotive industry continues to account for a quarter of the emissions of greenhouse gas substances (GHGs). Automobile emissions lead to a high concentration of air pollution, and many urban communities on the planet often do not meet the air quality indicators set by the World Health Organization (WHO) [104]. For many reasons, it is important to show off new energy vehicles in the global industry. Electric and hydrogen-powered vehicles offer many advantages for cities and urban areas, such as extremely low (hybrid electric cars with plug-in PHEV) to zero (electric cars with battery-BEV, electric cars with fuel cell-FCHEV, and hybrid fuel cell) tailpipe emissions, reduced noise, and the ability to enable new smart services [105–108].

Thus, the European Union (EU) is carefully and extensively studying the enforcement of a driving ban for diesel cars in other European and German cities [109, 110]. By doing so, policymakers want to reduce local emissions, such as nitrogen oxides, in order to mitigate natural and health problems [111, 112]. For example, in 2018, the German city of Stuttgart will impose restrictions on driving old diesel cars due to the higher nitric oxide content than in previous years [113, 114]. Furthermore, policymakers want to lower greenhouse gas emissions through alternative technologies, e.g., by using battery electric vehicles that are powered by sustainable energy sources to limit their environmental footprint. Since the road transport sector has generated 18% of the all greenhouse gas emissions over the past decade [115], an increased interest in alternative technologies such as battery electric vehicles (BEVs) could reduce such emissions [116].

6. EV Policy

Policy development for electric vehicles is an important factor for sustainable EV development. Most policy research has focused on plug-in electric vehicles (PEVs) in the short term, such as by (i) typically considering a wider range of evaluation criteria and (ii) setting PEV sales goals in the longer term (e.g., 2030 or 2040) [117]. Much evidence shows that the short-term method has played a key role in the supervision of PEV so far [118, 119]. Although some studies have shown that PEV and standard gasoline vehicles will eventually achieve equal costs (whether on the price tag or at any cost of ownership) [120, 121], various studies have shown

Table 1: Summary of key PEV supportive policies.

Policy demand focused	Description	Current PEV policy in Canada	"Strong" version
Financial incentives	Reduce the cost of PEVs and infrastructure (via grants, discounts, user fee exemptions, or tax breaks)	Financial incentives ranging from \$500 to \$14,000 per PEV in BC, QC, and across the country through 2020	Incentives of \$6,000 per PEV for 20 years across all provinces
High-occupancy vehicle (HOV) lane access	HOV lane access without restrictions for PEVs	PEVs in BC, ON, and QC have unrestricted access to the HOV lanes	Access to HOV lanes in all provinces that have them
Public charging	Allow charging while away from home	Current charger to gas station ratio unchanged over time	By 2025, the ratio of chargers to petrol stations will be 0.5 throughout all provinces
Building codes	Require charging access in new buildings	In BC, ON, and QC, charges are mandated by building codes	All provinces have adopted EV-ready building regulations
Carbon pricing	Increase in the cost of fuels that produce carbon emissions through cap and trade or a carbon tax	Existing carbon prices are in place in BC, AB, and QC; beginning in 2018, a federal price floor will be applied to all provinces	By 2030, the price of carbon reaches and remains at \$150
Supply-focused zero-emission vehicle (ZEV) mandate	Impose a minimum proportion of light-duty ZEV sales on manufacturers	Beginning in 2020, the QC ZEV obligation will increase to 22.5% credits by 2025	By 2040, a national ZEV requirement will have increased market share by 40%
Vehicle emission standard	Give light-duty cars a maximum amount of tailpipe emissions	By 2025, the fleet must meet an average CO_2e/km standard	By 2040, the fleet must emit 71 g CO_2e on average
Low-carbon fuel standard	Demand that fuel suppliers limit the amount of carbon in the fuels they sell and provide credits for the use of alternative fuels (such as electricity and hydrogen)	By 2030, national standards call for a 12.5% decrease in the carbon intensity of transportation energy compared to 2010	According to national standards, the carbon intensity of transportation energy must decrease by 45% by 2040 compared to 2010 levels and by 25% by 2030

Table 2: Policy on recycling and recycling technology for metal recovery from end-of-life batteries of EVs.

Country	Key content	Company	Recycling process	Reference
European Union	Create a system of collection and recycling for all types of batteries based on an extended producer responsibility system through the Battery Directive	GRS Batterien Batrec AG	Pyrometallurgy, mechanical separation, hydrometallurgy	[136–138]
Swiss		Eurodieuze Recupel	Pyrolysis, hydrometallugy, hydrometallurgy, mechanical separation, leaching, and refining	
France		SNAM	Crushing, pyrolysis, distillation, pyrometallurgy	
Spain		Pilagst	Mechanical separation, chemical treatment	
Belgium		Umicore	Hydrometallugy after pyrometallurgy	
Germany	The German Batteries Act requires all producers and importers of batteries and accumulators to collect end-of-life batteries	Accurec	Pyrolysis, hydrometallurgy	[138, 139]
USA	Universal waste regulations are used to manage the large number of batteries. The recycling of EV batteries at the end of their useful lives is not required by federal law, though. Several states recently outlawed the disposal of used EV batteries in landfills	Onto Retriev TOXCO	Cryogenic crushing, hydrometallurgy, pyrometallurgy, cryogenic crushing, hydrometallurgy	[138, 140]
Japan	Under the Law for the Promotion of Effective Utilization of Resources, manufacturers encourage resource collection and recycling on a voluntary basis (recycling batteries is not covered by any specific laws)	DOWA Sumitomo	Pyrometallurgy, hydrometallurgy, hydrometallugy after pyrometallurgy	[141, 142]
China	Interim Measures for the Management of Recycling and Utilizing Power Batteries for New Energy Vehicles were published in China (including design, production, and recycling responsibilities)	N/A	N/A	[143, 144]
Korea	After receiving a subsidy, the consumer must return the EV's dead battery. The recycling of EV battery end-of-life batteries is not, however, subject to any laws	SungEel Hitech Kobar	Hydrometallurgy	[145, 146]

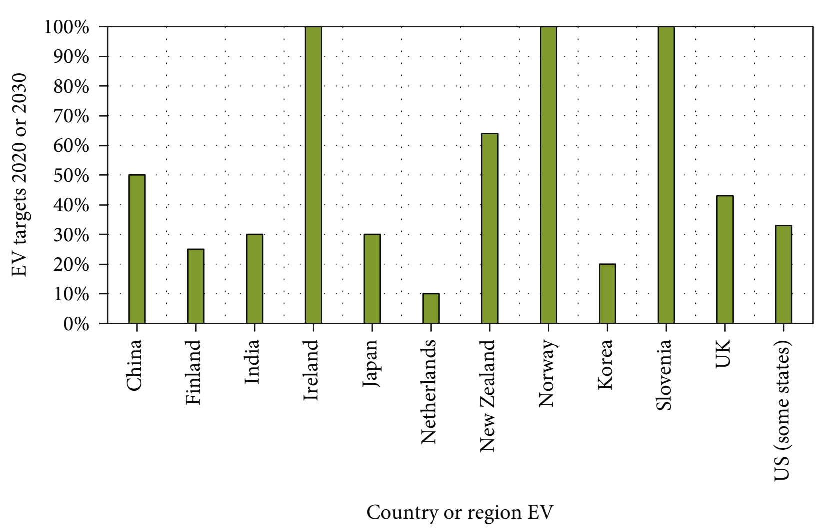


Figure 13: EV present and future targets by countries.

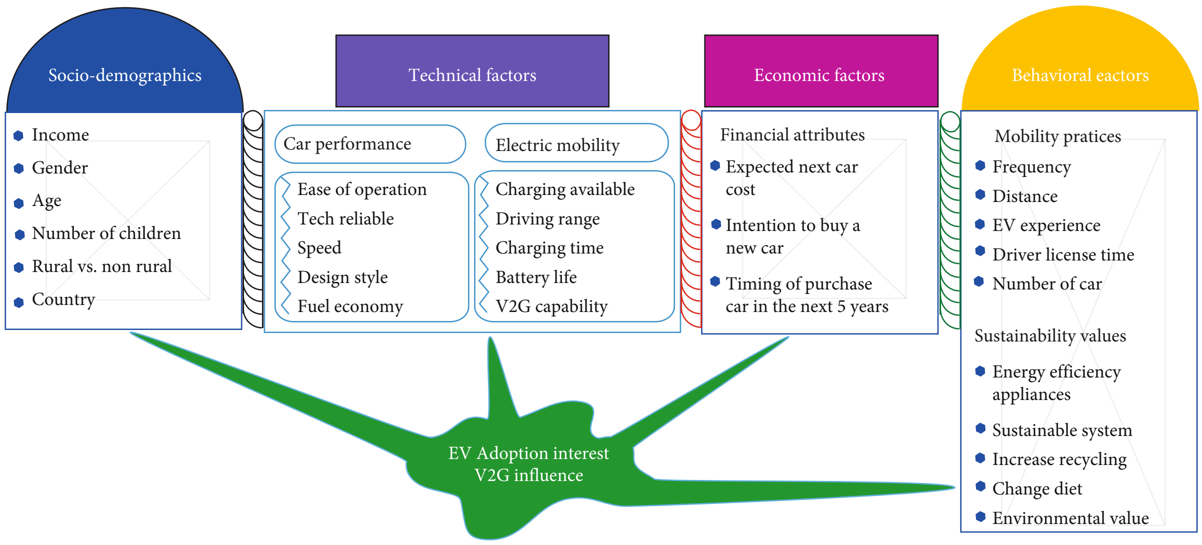


Figure 14: Conceptual framework for EV adoption and the influence of V2G [149].

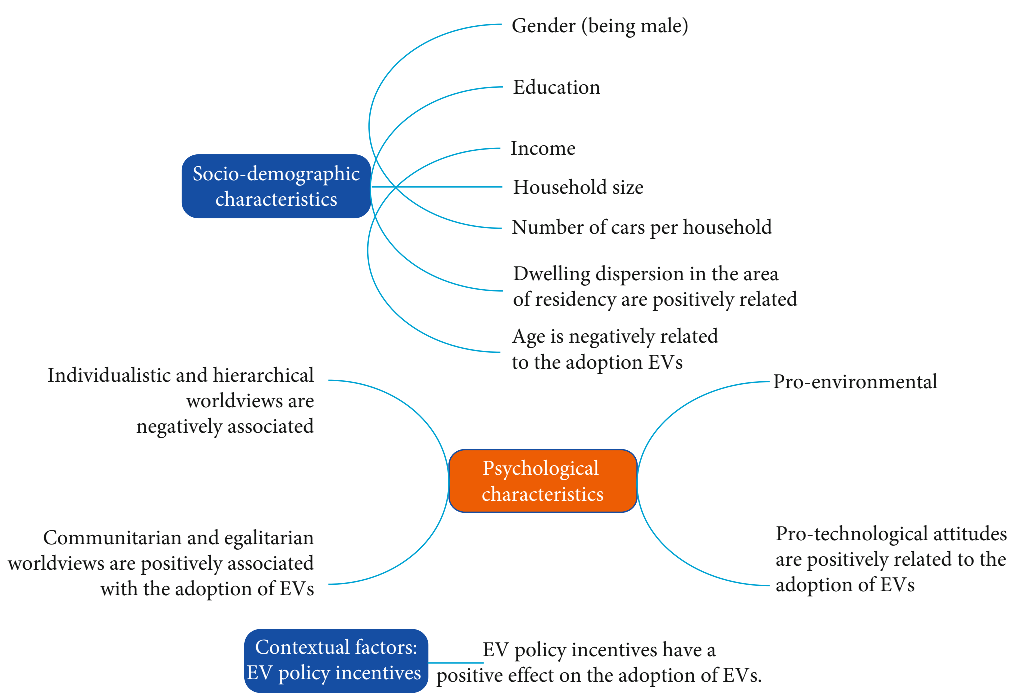


Figure 15: EV adoption hypothesis stature.

that this strategy will undoubtedly help to expand PEV transaction volume. In the coming decades [122, 123], for example, a Canadian study showed that despite ideally reducing battery costs, without expanding at least one stable PEV, the new industry-wide PEV cannot exceed 10% by 2030 [124]. However, the current vehicle market has already switched to new BEV technology and will soon go for FCEV. Most national policies around the world are focused on reducing road transport CO_2 emissions by shifting to high energy efficiency and low-carbon energy demand technologies. According to the International Renewable Energy Agency (IRENA), renewable energy policies must prioritize end-use sectors over power generation. Renewable heating and cooling require more policy attention, such as dedicated targets, technology mandates, financial incentives, generation-based incentives, and carbon or energy taxes [125]. EV and climate policy also push to utilize renewable energy in the transportation sector. To reduce more emissions from the road transport sector, the

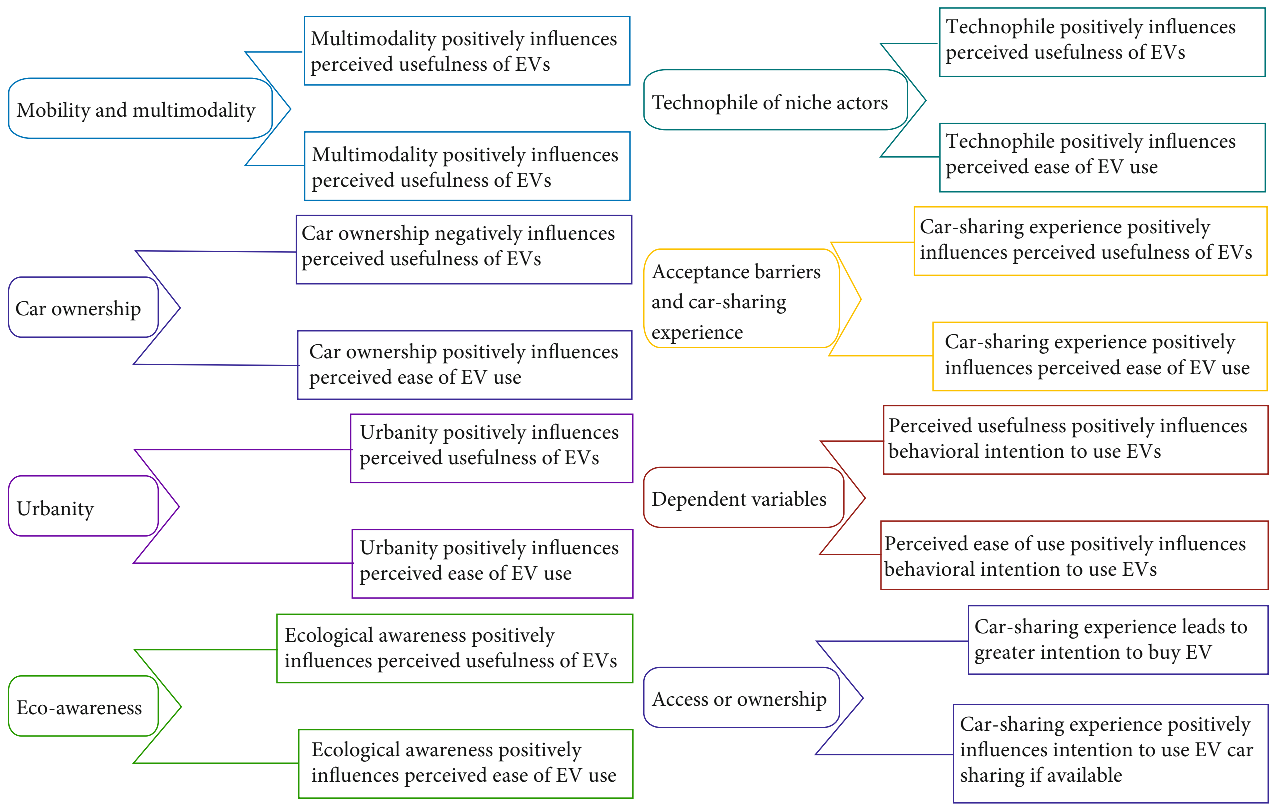


Figure 16: A mobility research framework.

subnational government has implemented several initiatives to stimulate the adoption of electric mobility in recent years [126].

6.1. Barriers to Adoption. PEV adoption is low in most regions due to a variety of demand and supply-side market barriers [127, 128]. Understanding these barriers is helpful for designing policies to encourage EV adoption. Previous studies have identified eight key types of PEV stabilization policies implemented in Canada and various sites, which can measure their impact on PEV adoption [129]. These policies can be predicted using core policies implemented globally and form the basis of most PEV strategies (e.g., [130, 131]). For a small part of the entire industry, different types of policies were deemed to have a negligible to small market share impact (e.g., voluntary programs) and/or a particularly uncertain impact (e.g., research and development support) [117, 132]. These eight "quantifiable" policies are described in Table 1, along with how they are currently being implemented in Canada and how they differ from a "strong" version that we summarized in this paper.

Table 1 shows an example, but it is true that EV adoption needs strong policy support to overcome its barriers to adoption. We can utilize the developed countries' EV policies (e.g., PEV policies) and their impacts to make reliable policies that could be linked to climate policies. However, EV policy is still experiencing challenges because consumers need time to adopt new technology. In this next section, we summarized some countries' EV policy improvements and future goals.

6.2. The Major Improvements of the 2018/19 Agreement Include the following Policies

(1) The EU has approved some excellent strategic tools. They include mileage standards for cars and trucks and the Clean Electric Vehicle Directive, which stipulates the public procurement of electric vehicles. The Energy Efficiency Directive specifies minimum requirements for load foundations in new and rebuilt structures

(2) In China, the progress of the agreement reviewed the speculative restrictions on the new ICE car manufacturing facility and brought forth a proposal to establish normal mileage for the passenger light-duty vehicle (PLDV) in 2025. The utilization of separate motivating inducements for vehicles depends on the quality of the battery (for example, a car loan and a zero-emission car loan under the new energy vehicle rules)

(3) In Japan, the adoption of an automatic method, which can be used by modern partners, means that the emissions of greenhouse gas (GHG) substances from vehicles (including sold vehicles) provided by car manufacturers to households account for 80% of the country (road vehicles account for 90%), through the combination of HEV, BEV, PHEV, and FCEV, to reduce emissions in 2050. The truck's performance principles have been revised, and an update on the vehicle's mileage has been announced

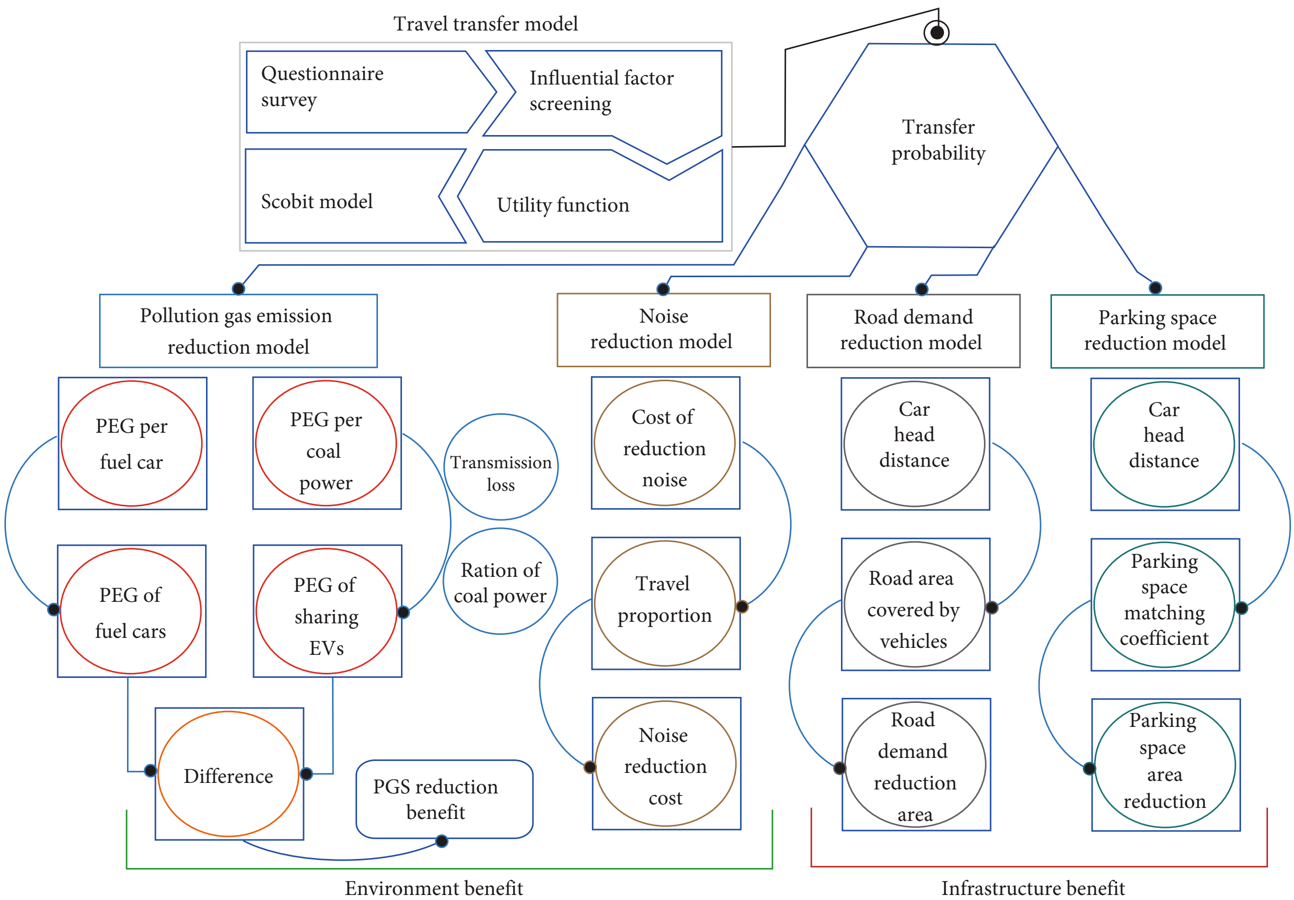


Figure 17: Travel transfer model [158].

(4) Canada has realized the dream of combining EVs with new methods. British Columbia announced the introduction of the world's most potent ZEV (zero-emission vehicle) team: by 2030, the share of the ZEV business will reach 30%, and by 2040, it will reach 100%. Canada's system is comparable to the ten US states where the ZEV team has been implemented

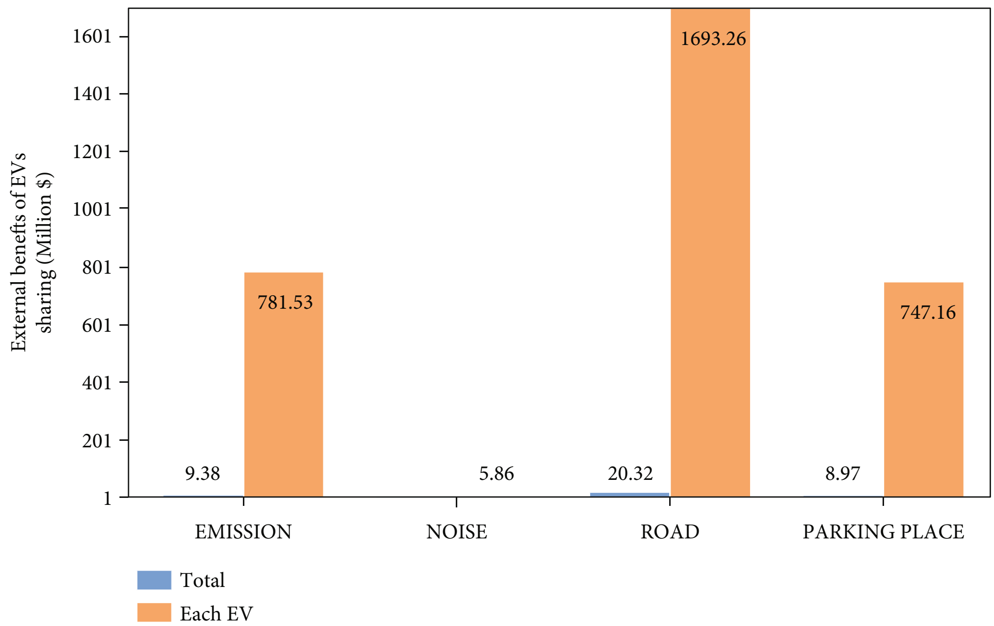
(5) India announced the second conspiracy period, "Faster Adoption and Manufacturing of Electric Vehicles in India" (FAME India). It reduced the price of electric vehicles by half, focusing on vehicles for open or general transportation (vehicles, rickshaws, and taxis) and private bicycles

(6) In South Korea, the level of national sponsorship for all low-carbon vehicle purchases increased from 32,000 in 2018 to 57,000 in 2019, and other strategic tools have been added, including public access, subsidies, and discounts on transportation security fees and reduced parking spaces. It is joined by an objective to support production volume of more than 10% of the capacity of all vehicles by 2022 and to use money-related help and progress to guarantee great manufacturing players

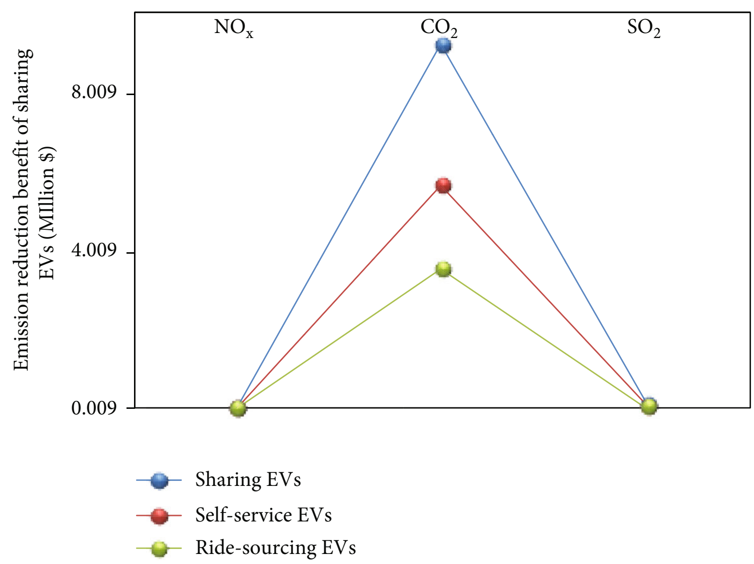
Strategic energy is also increasing in various countries. One of the most important aircraft types is Chile, which is one of the largest airlines in the world after China. Chile's goal is to rejuvenate 100% of its convertibles and 40% of its private cars by 2050. New Zealand also has high expectations and hopes to achieve a transition from a clean economy to zero emissions by 2050. New Zealand and Chile joined the Electric Vehicle Initiative (EVI) in 2018 [133].

6.3. Policy on Recycling of EV Battery by Countries. Battery-related research is also important to enhance EV adoption. This is part of waste management and needs a specific policy to encourage the expansion of the EV market. With the rise of the EV market, the global supply of EVs has recently increased significantly, as has the global market for EV batteries [134]. China, Japan, and Korea have a large market share of EV batteries and are essential countries for the development and production of EV batteries on a global scale. Because the top ten EV battery producers are from China, Japan, and Korea, they accounted for more than 80% of the EV battery supply in 2018 [135].

To maximize resource recovery and properly manage hazardous materials from end-of-life EV batteries and technology, recycling policies for EV batteries are being implemented in several countries, as shown in Table 2.



(a) External EV sharing benefits in Chongqing



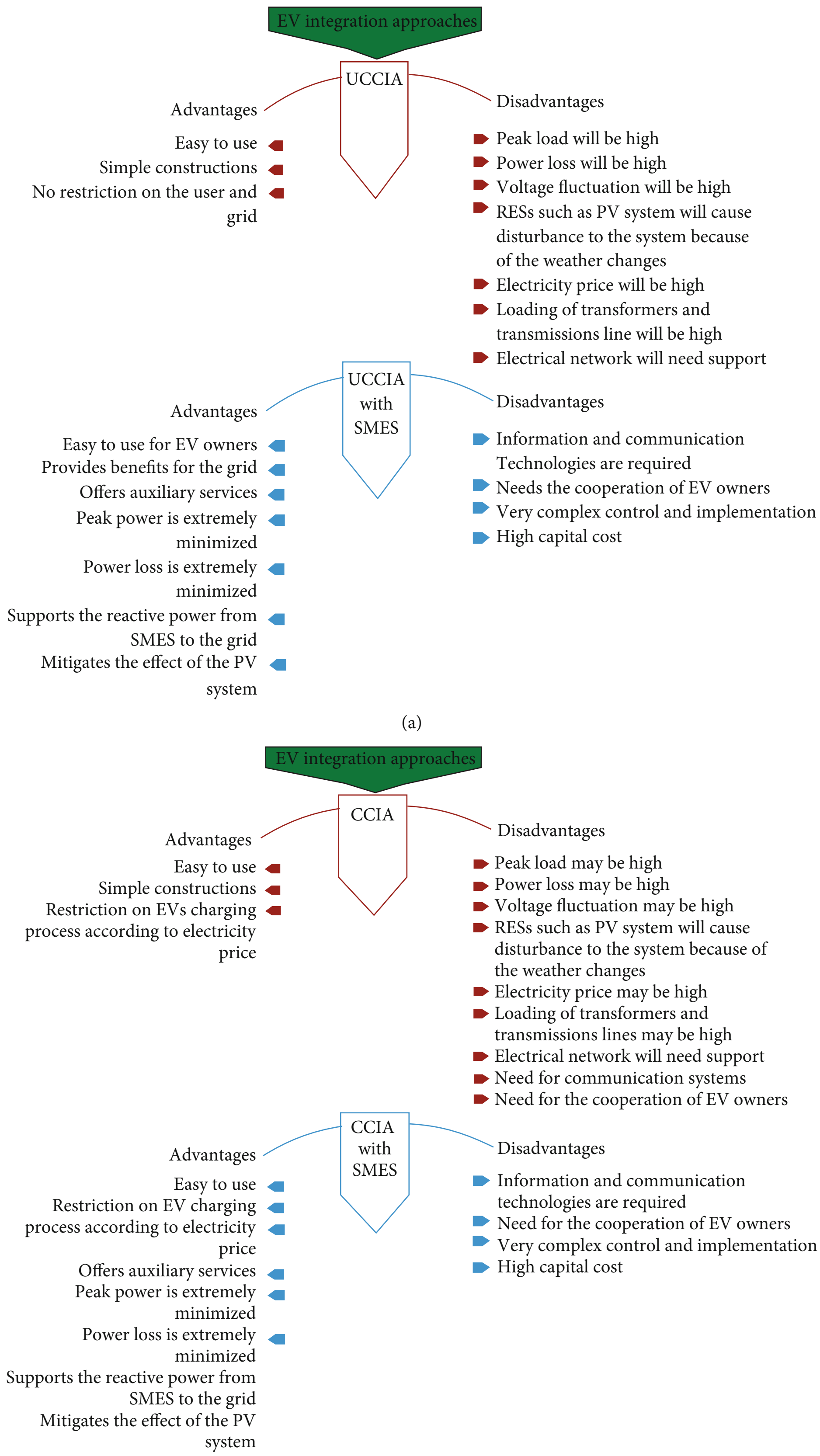
(b) Emission reduction benefit of sharing ENs

Figure 18: EV sharing benefits [158].

6.4. EV Adoption. EVs continue to penetrate the national market, and by the end of 2018, more than 5.1 million EVs had been produced [147]. Global stocks of EVs have mainly been concentrated in three regions: China accounts for about 45% of them, followed by Europe and the United States, which account for 24% and 22%, respectively [133]. In addition, European countries continue to travel relative to the entire fleet. More than 10%, of vehicles in Norway are electric vehicles (BEV or PHEV), followed by Iceland (3.3%), the Netherlands (1.9%), Sweden (1.6%), and China (1.1%) [148]. However, China has the most widespread advertising for EVs, and by the end of 2018, its national fleet increased by 1.1 million EVs [133]. This can be observed in the international EV targets for 2020 or 2030 in Figure 13.

The literary outcomes integrate the appeal of EV choices and the six components of the V2G influence. The text on the EV and (to a lesser extent) the evolving V2G employment classification typically emphasizes the importance of six dimensions, including the various parts of the user, conventional vehicles, and a supportive (and social) foundation for innovation. An overview of these indicators can be seen below. Figure 14 shows a multidimensional conceptual framework for EV adoption [149].

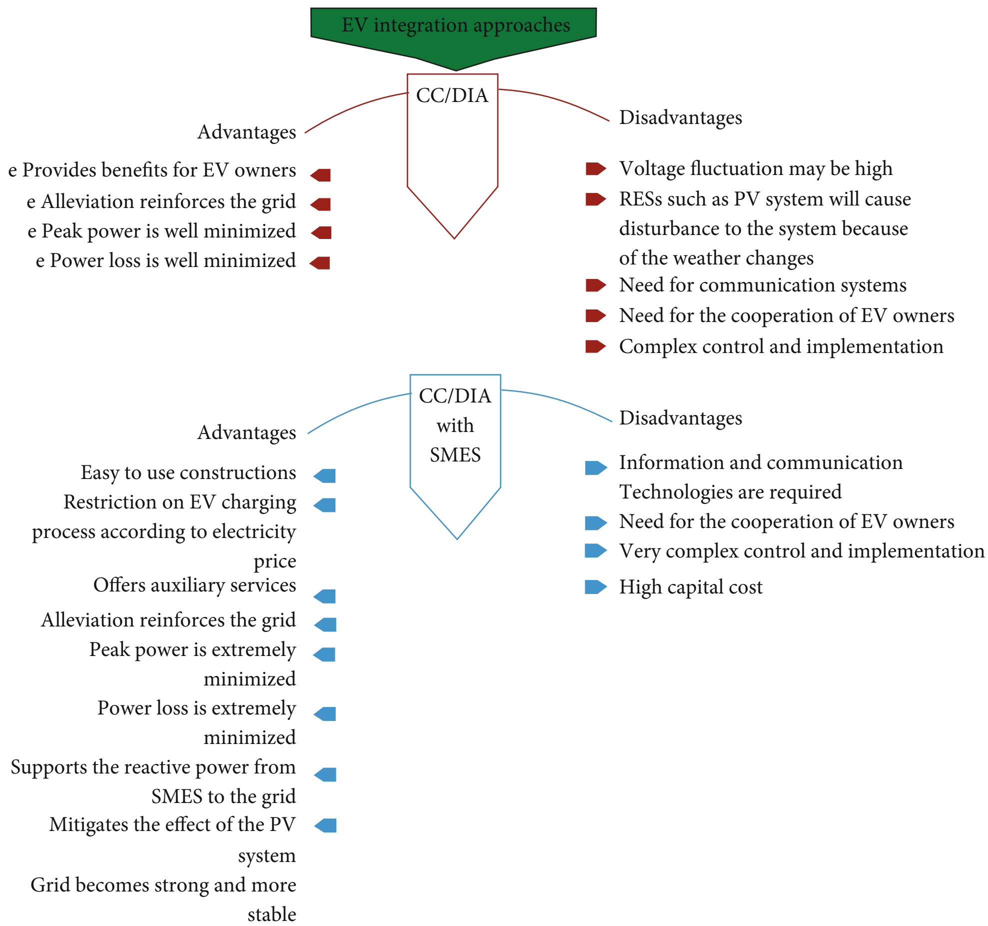
6.5. EV Adoption Hypothesis. The current study has reliably established that early users of EVs have the quality of social segmentation and can be clearly identified on the basis of potential users or non-EVs (i.e., buyers of ICE cars). Currently, the study



(a)

(b)

Figure 19: Continued.



(c)

Figure 19: Advantages and disadvantages of the EV integration approach.

assumes that regular or early users (depending on definition) usually (1) are profoundly trained [150], (2) have a higher income [151], (3) are young to middle-aged [152], (4) are part of a family with several cars [150, 153], (5) live in larger families [150], (6) are mostly men, and (7) live in small- and medium-sized cities [152]. Figure 15 shows a diagram of the EV adoption hypothesis.

The latest report by Nayum et al. [150] tested the importance of psychological factors as an indicator for buyers who buy increasingly environmentally attractive vehicles (e.g., electric cars). They expanded the comprehensive action determination model [154], which includes targeted, standardized, situational, and ongoing impacts on environmentally friendly behavior [64, 155].

6.6. EV Sharing. Given the dangers of climate change, the mobility sector must move towards sustainability. One way to reduce emissions while driving is to establish the use of electric vehicles (EVs). However, given the current market share in Germany, the expected regime change from traditional combustion to electric motors seems rather unlikely. This leads to the search for new options for dynamic market growth. Recent studies have shown that consumers lack sufficient knowledge and have a high level of uncertainty regarding electric vehicle technology. To overcome these barriers to acceptability, this study suggests that experience with car-sharing services—in particular electric car-sharing—can lead to broader adoption of electric car technology, which will lead to wider market penetration. Using the technology acceptance model, a quantitative study was conducted between users who share cars and those who do not to evaluate the impact of car-sharing experiences on the acceptance of EVs. In addition, five possible predictors for the adoption of EVs were tested: mobility, automotive ownership, urban areas, environmental awareness, and technology [156]. Figure 16 shows the car-sharing mobility structure.

6.7. Measuring Frame. According to Pigou's theory, external factors must be assimilated to reflect their real expense or value [157]. As a combination of new, environmentally friendly technologies and an innovative business model, the external effects of sharing electric cars should undoubtedly be studied in order to facilitate this further. Selecting appropriate indicators is a crucial step. The entire structure of the travel transfer model can be observed in Figure 17 [158].

Summarizing the above findings of this document by sharing travel measurements of EVs instead of urban ICVs reveals some interesting results. For example, in China, in Chongqing, 6.33% of urban residents might want to move their travel arrangements from ICVs to self-service EVs, while 4.26% of people want to choose EVs from ICVs. This conclusion means that self-service EVs are currently more popular on the market than self-service EVs. The potential market demand for EVs is 27,400, and the demand for EVs with a source code is 12,000. Based on the results, the external benefits of sharing EVs can be calculated (Figure 18(a)). The most significant benefit comes from the highway asset reserve and the benefit of parking. The benefits of reducing emissions are primarily related to reducing carbon dioxide emissions, as shown in Figure 18(b) [158].

7. Advantages and Disadvantages of Electric Vehicles

Recently, some analysts have uncovered the critical advances in EVs. Nordelöf et al. [159] written survey analyzes knowledge points based on the life cycle assessment as advantages of EVs and shows the continuous development of electric vehicle innovations, the constant progress in material production, and the age of performance the life cycle assessment EV test [159]. They found that many articles consider the energy source to be the driving force behind the EV results, but they also argued that many inspections could not undo this judgment, resulting in people having no rational information about the environmental impact of EV [160]. ICEV were compared to shortages in the concentration of GHG or EV. WHO conducted an important WTW study focusing on EVs [161]. Figure 19 shows a comparison of EV integration approaches [162, 163], where SMES is the superconducting magnetic energy storage, UCCIA is the uncontrolled charging integration approach, and CCIA is the controlled charging integration approach.

8. Conclusions and Recommendations

EVs can effectively promote the use of renewable energy and environmental pressures on ICE vehicles. This paper explores EV-related technology and major policy concerns to help make EV a sustainable development. The following conclusions are drawn.

(1) The estimation of EV technology improvement in this study indicates that the higher complexity of sustainable development leads to relatively slower EV adoption

(2) A possible implication for the policymakers encouraging EV development is to issue more incentive plans for innovations in the grid and electric vehicle relationship domains

(3) The technology trajectories of future development models have been proposed for EV wireless charging and energy networks. This could be a recommended model for the future development of EVs and energy structures. Moreover, power electronics for EV integration on the grid have negative impacts. The results in the paper prove that it is time to approach EV charging to reduce negative impacts

(4) The policymakers found that EVs might be a renewable energy contributor to reducing CO_2 emissions. However, EV sustainable development needs strong policy support, which has been proposed in our review paper. We summarized different countries' strategies, methods, and outcomes to give attention to EV sustainable development

Although this work provides insight and novel results and discussion about the technological and policy development of EV, there are still some limitations. For instance, depending on the application, there are two different types of EV. The car is one, and "the bus, truck, and lorry" are the others. Exploring and contrasting the technological developments in the domains of these two types is important from an application standpoint. We use the common method system to decompose the EVs filed in the work, even though it currently appears impossible to achieve sustainable development, but this work will provide a full package to understand barriers and necessary methods to solve them. Thus, this study provides a number of policy recommendation to address the increase of the EV adoption by showing EV uptake and promote the installation of charging stations or act to remove barriers and limitations.

(1) The provincial government provides incentives to EV users, such as cash rebates or subsidized loans, to help them offset the cost of the electrical vehicle supply equipment (EVSE) and its installation as well as the costs of the necessary building upgrades

(2) Provide financial assistance to landlords and strata councils with a requirement for a specific number of charging stations

(3) Municipal and provincial governments should develop and implement a program within the next ten years to encourage and provide financial support to strata councils and landlords who develop retrofit plans and upgrade the power distribution systems of their buildings to meet residents' future charging needs

(4) Avoid being overly conservative, which can result in the unnecessary oversizing of electrical equipment, and revise and update the regulatory requirements from codes and standards on a regular basis to reflect the most recent technological advancements

(5) To prevent future situations of unfairness and inequality among them, regulate the rights and responsibilities of EV users, building residents, strata councils, and landlords regarding the installation and use of charging stations within multiunit residential buildings (MURBs)

(6) Expand the current guidelines to offer precise direction and answers on technical and governance issues like defining ownership and charging infrastructure costs

(7) Develop a program or guideline to instruct and direct strata councils and landlords on how to create a long-term EV charging infrastructure plan that will

direct and dictate present and future charging infrastructure deployment in their building, the need for infrastructure upgrades, and governance and ownership considerations

Data Availability

Data can be available upon request to the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Electric Kickboard Demand Prediction in Spatiotemporal Dimension Using Clustering-Aided Bagging Regressor

Prince Waqas Khan, Se-Joon Park, Sang-Joon Lee, and Yung-Cheol Byun

Department of Computer Engineering, Jeju National University, Jeju-si, Republic of Korea

Correspondence should be addressed to Sang-Joon Lee; sjlee@jejunu.ac.kr and Yung-Cheol Byun; ycb@jejunu.ac.kr

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Demand for electric kickboards is increasing specifically in tourist-centric regions worldwide. In order to gain a competitive edge and to provide quality service to customers, it is essential to properly deploy rental electric kickboards (e-kickboards) at the time and place customers want. However, it is necessary to study how to divide the region to predict electric mobility demand by region. Therefore, this study is made to more accurately predict future demand based on past regional customers' electric mobility demand data. We have proposed a novel electric kickboard demand prediction in spatiotemporal dimension using clustering-aided bagging regressor. We have used electric kickboard usage data from a Jeju, South Korea-based company. As a result of the experiment, it was found that the accuracy before using clustering-based bagging regressor and when the region was divided by the clustering method, the performance was improved, and we have achieved a regression score (R^2) of 93.42 using our proposed approach. We have compared our proposed approach with other state-of-the-art models, and we have also compared our model with different other combinations of bagging regressors. This study can be helpful for companies to meet the user's demand for a better quality of service.

1. Introduction

With the increasing demand for fuel-efficient vehicles, due to growing concerns about greenhouse gas and carbon emissions, the use of electric kickboards and scooters is expected to increase over time. Since 2016, the penetration index of this sharing-service acceptance rate has been growing [1]. In addition, the need for sustainable urban mobility and modern transportation infrastructure is leading to a shift from traditional modes of transport to electronic modes of transport. Demand for this electric mobility has grown significantly. An electric kickboard is a two-vehicle device. People can ride it while standing on it. It is suitable for one and a maximum of two persons. Figure 1 shows a picture of an electric kickboard.

Electric kickboards (e-kickboards) are expected to affect energy security and air quality positively. As industry 4.0 develops, companies have begun to study how to use big data, which is a collection of previous data, to meet customer needs. Such big data only applies to companies that have continued to operate, and for startups starting a new business, most of the data is small in amount and unstable in the form of income [3]. It is difficult to meet customer needs with insufficient qualitative and quantitative data. Customers who want to use electric mobility feel satisfied with using the service without being restricted by time and place when they want to use it. However, suppose it cannot be used due to finite electric mobility. In that case, customers may feel inconvenient, and if this case continues for companies, demand will decrease, which may affect sales [4]. That is why companies need to place them where and when customers want them.

This study used data from an e-kickboards company that provides electric mobility services in Jeju Island, South Korea. Figure 2 shows the location of kickboard stations in Jeju Island, South Korea. Tourists or local residents can rent a kickboard from these stations. Since there is nothing more important than safety, the company also provides free

Figure 1: Electric kickboard [2].

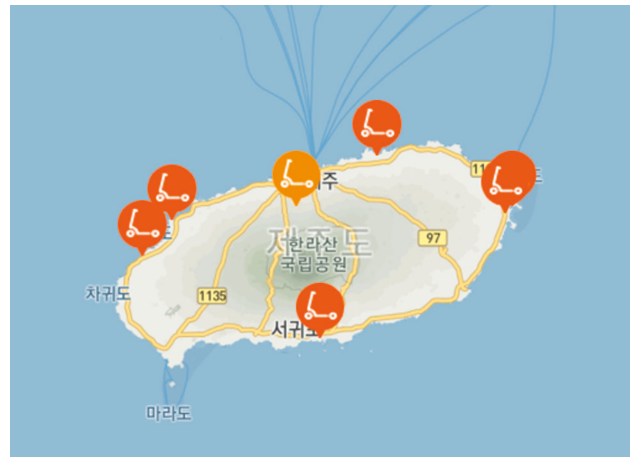

Figure 2: Rental locations of kickboard in Jeju Island.

helmets and safety gear. The top speed of the kickboard is 25 km/h.

Deploying through demand forecasting may introduce errors. If electric mobility is insufficiently deployed, this gap can be filled by bringing it from where there is a surplus of demand. However, the longer the distance between the two regions, the longer it will take to serve customers. Based on this idea, this study can also enhance prediction results by dividing the regions in Jeju Island, placing electric mobility with remaining demand in the center of each region, and quickly relocating where errors occur. In this article, when dividing the area in Jeju Island into several places, nearby rental stations were bundled based on the centroid, and electric mobility demand prediction was carried out. Electric mobility is stored in the center of each region. If a region with more demand than predicted through regional forecasting occurs, quick service can be provided by fetching and deploying electric mobility in the region's center. In addition, it was confirmed that the prediction accuracy was increased when the learning results were compared before and after dividing the regions.

1.1. Contributions. We proposed to use a clustering-aided bagging regressor for electric kickboard demand prediction in spatiotemporal dimensions. We used the k-means algorithm to cluster e-kickboard demand areas and identify the centroid and then used a bagging ensemble for demand prediction. The proposed bagging ensemble consists of a base layer and metalayer. The base layer consists of XGBoost, Extra Trees regressor, and Random Forest model, whereas the metalayer consists of an Extra Trees regressor. The significant contribution of this article can be summarized as follows:

(i) Integrating spatial, temporal, and weather data to cover the effect of different parameters on the mobility demand

(ii) Employing data and predictive analytics techniques for data obtained from electric kickboard company

(iii) Integrating clustering and bagging regressor to develop a hybrid prediction model to predict e-kickboard demand

(iv) Comparing the proposed model with state-of-the-art ML models and different combinations of ensemble models

The rest of the article is arranged as follows. Section 2 presents the relevant approaches and publications and compares existing literature and proposed methodology. Section 3 introduces the methodology used in this research study. Section 4 presents an analytical and graphical analysis of data. Section 5 provides results and covers comparisons with the latest machine learning models. Finally, we conclude the article in Section 6.

2. Related Work

Different machine learning models have been used by researchers, such as long short-term memory (LSTM), Generalized Autoregressive Conditional Heteroskedasticity

(GARCH), Seasonal Autoregressive Moving Average (SARIMA), Bidirectional Encoder Representations from Transformers-Based Deep Spatial-Temporal Network (BDSTN), Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN), hexagonal convolution operation LSTM (H-ConvLSTM), and Dynamic Spatiotemporal GNN method with Tensor Network (DSTGNN). Table 1 shows the contributions of this research in the context of the literature.

2.1. E-Mobility Data Analysis Using Deep Learning. Greenhouse gas emissions (GHG) and high fuel consumption have become a significant issue these days [14]. In particular, CO_2 emissions from transportation have reached almost a quarter of global emissions [15]. The electric vehicle (EV) is considered an exciting alternative to solve the above problems [16]. However, issues such as inadequate billing infrastructure have also arisen to support the growing demand in the growing EV market. Effective forecasting of commercial EV bill demand ensures the reliability and stability of short-term network utilities and supports investment planning and resource allocation for long-term infrastructure bills. The article by Yi et al. [17] provides an overview of the monthly commercial EV load application time series using the deep learning approach. The proposed model was confirmed by original datasets in Utah and Los Angeles. Two forecasting purposes, one-step forward forecasting and multistep forward forecasting, were reviewed. In addition, the model was compared to other time series and machine learning models. Experiments show that both Seq2seq and LSTM provide satisfactory one-step predictions. However, when making multistep predictions, the Seq2seq outperforms other models in terms of various performance measurements, demonstrating the model's powerful ability to predict sequential data.

The study by Zuniga-Garcia et al. [18] considers the issue of the use of travel data in the mobility data specification standard for meaningful analysis of the use of the infrastructure of e-scooters without the use of personally identifiable numbers. They examine the integration of e-scooters into the city infrastructure of Austin, Texas, using e-scooter supplier travel data and infrastructure geographic inventory data. Their analysis shows that e-scooters use about 80,000 e-scooter rides each year, more than 11 million, which is 1.4 percent of the total electric scooter rides in the city during this period. Their results show that the average distance traveled by electric scooter was divided between pedestrians (18 percent), bicycle lanes (11 percent), roadside (33 percent), and other nonspecific locations (38 percent). In addition, about sixty percent of road trips were made on large arteries, and bicycle lane users prefer moderate to high comfort levels. The purpose of the article by Davies et al. [19] is to examine the current distribution and development challenges of tourist destinations, focusing on micromobility. Micromobility is linked to a new model that includes but is not limited to hiking, cycling (both current modes), e-bikes, and e-scooters (new modes). The proliferation of new micromoles in destination urban areas can be viewed positively in terms of their sustainable urban dynamics, thus increasing the chances of attracting tourists. However, it is also pessimistic about potential issues with space, accessibility, and sustainable implementation. Therefore, destination developers and partners need to consider successfully integrating micronavigation into a sustainable transportation system.

2.2. E-Scooter Demand Prediction. The study by Bai and Jiao [20] provides empirical evidence of e-scooter travel in two US cities. Moreover, transportation and training literature compares the two cities and emphasizes the importance of local individuality. The results of the regional analysis show that electric scooters were widely used in the city center and on the university campus. However, patterns of electric scooter use in both cities were temporarily different: Austin faces more electric scooter congestion during the day and weekends, while Minneapolis shows large rides at night and throughout the week. In the article by Feng et al. [21], they used a large amount of different Twitter data—including text; references; GPS data; general images; and e-scooter app screenshots, emojis, and emoticons—to analyze electric scooter racing services. Over the past 18 months, more than 5 million English tweets referring to the word "scooter" or scooter emoji have been added. They first did extensive data preprocessing to eliminate noise and reduce false positives. They believe that the results obtained by the public will provide a deeper insight into the emergence of e-scooter services as a generic directory in smart cities. The study by Kolaković-Bojović et al. [22] provides a quantitative and qualitative analysis of the data by pointing out the critical issues presented in both newspapers and Twitter posts. They conducted media readings on its effects on various aspects of its environmental well-being. The authors examine, among other things, the use of electric scooters in the press and the challenges to civic security, as well as the relationship between the posts of the Twitter community in Serbia. In general, they tried to answer whether electric scooters can be considered a security challenge in the city or any other issue of moral fear.

2.2.1. Bus Arrival and Departure Time Prediction. There is always some uncertainty about public buses' arrival and departure times, such as signals, bus stop times, climate change, and fluctuations in travel requirements [23]. In developing countries, this uncertainty is heightened by the availability of redundant vehicles, different modes of transportation, and a lack of risk discipline. Therefore, the issue of forecasting remains a challenge, especially with the arrival of buses in developing countries. The work by Achar et al. [24] suggests a new way of predicting the arrival of buses in real time. Unlike the current method, the proposed method learns transport interactions and patterns. It first recognizes the unknown sequence of spatial dependencies and then understands the linear, non-static spatial correlation for this discovered sequence. It retains the temporal relationship between continuous travel and changing time. The learned prediction model is rewritten in an appropriate

Table 1: Comparison of recent research contributions for vehicle demand prediction.

Sr#	Ref, year	Clustering	Regression	Proposed model	Vehicle type	Weather	Area
1	[5], 2018	Yes	No	Hierarchical clustering	E-scooter	No	Germany
2	[6], 2019	No	Yes	LSTM	Taxi	Yes	Xiamen and Chengdu, China
3	[7], 2020	No	Yes	GARCH, SARIMA	E-scooter	No	Thammasat University, Thailand
4	[8], 2021	No	Yes	BDSTN	Taxi	Yes	New York, USA
5	[9], 2021	Yes	No	HDBSCAN	E-scooter	No	Berlin, Germany
6	[10], 2022	Yes	Yes	LSTM	E-scooter	Yes	Seocho and Gangnam, South Korea
7	[11], 2022	No	Yes	Random Forest	Car, bicycle	No	Hamburg and Hanover, Germany
8	[12], 2022	No	Yes	H-ConvLSTM	Car	No	Chengdu, China
9	[13], 2022	No	Yes	DSTGNN	Bike, taxi	No	New York, USA
10	Proposed	Yes	Yes	Bagging regressor	E-kickboard	Yes	Jeju, South Korea

linear state-specific format to make the best predictions come true, and then the Kalman filter is applied. Performance was analyzed using actual field data and compared with existing methods.

2.2.2. EV Power Demand Prediction. The study by Tianheng et al. [25] outlines the power demand forecasts for electric vehicles and the strategy for overcoming errors in forecasting. The goal is to reduce fuel consumption in real-time operations. They develop a neural network model to estimate the vehicle's electricity demand. Furthermore, a mathematical model is proposed to convert the predicted power demand into a battery charge status reference, greatly simplifying the charging programming system. Finally, they use the adaptive equivalent consumption minimization strategy to monitor referrals and determine the status of the propulsion system. The proposed approach enables the maximum distribution of power between engines and cars worldwide and maximum torque distribution locally. The simulation power-sharing plug-in was performed on a hybrid electric bus. Compared to rule-based and proposed technologies, the proposed method has significantly improved fuel consumption and other indicators.

2.3. Taxi Demand Prediction. Taxi demand forecasts have recently attracted increased research interest. In the article by Liu et al. [26], they presented challenging and award-winning work entitled Taxi Origin-Destination Demand Forecast, which aims to predict the demand for taxis across all regions at a later interval. The critical challenge was effectively acquiring various relevant kinds of information to learn the types of questions. They addressed this issue using the new contextual spatial time network to model the local spatial context, the temporary evolutionary perspective, and the global communication perspective. Extensive testing and analysis of a large database demonstrated the high efficiency of their contextual spatial time network model compared to other methods for predicting the actual destination needs. Real-time and precise taxi demand forecasts can help drivers in booking taxi resources for the city in advance, help drivers find passengers faster, and reduce waiting times. Many current studies have focused on the local and temporal characteristics of taxi demand distribution, with a lack of a model of the relationship between taxi pick-up demand and download demand from a multipurpose learning perspective. In the article by Zhang et al. [27], they proposed a multifunctional learning model with three parallel LSTM levels for predicting and downloading taxi demand and the single demand for performance prediction methods and two on-demand prediction methods. Experimental results from datasets show that the demand for collection and the demand for downloads depend on each other and the accuracy of the suggested co-deduction system.

Taxi demand forecasting plays an important role, especially in ranking resources to help differentiate between demand and service in times of economic sharing and autonomy. However, many studies have sought to exclude complex local-world patterns of taxi demand from the historical taxi demand threshold, effectively ignoring the underlying effects of regional activity and effectively mobilizing long-term cycles. In the article by Cao et al. [8], they note two significant observations; one is that the pattern of taxi demand varies significantly between different active areas, and the other is the demand for taxis following dynamic daily and weekly patterns. To address these two issues, they proposed a new bidirectional encoder representation-based deep spatial-temporal network that captures locations of interest that define regional functions and include multiple local and indicates complex local-temporal relationships with global features. Bidirectional encoder representations-based deep spatial-temporal network' points of interest have introduced a time-space adaptive module to capture taxi demand's complex time-space pattern and dynamic time phases. Points of interest have implemented a functional agreement implantation module in all regions. To their knowledge, this is the first time the proposed architecture has been used to determine the types of taxi claims, and this is the first time they have considered the practical similarities. Their research results with the New York City Real Traffic Database show that the proposed method implements more complex methods and their suggested model is much better than other methods.

In the article by Xu et al. [28], they suggest a sequential learning model that can estimate the demand for taxis in different areas of the city depending upon current demand and other relevant information. It is essential to consider the advanced information here as future taxi applications will be linked to past activities. For example, anyone requesting a taxi at the mall can request a taxi to reach home within hours. They use LSTM, an excellent sequential learning system, to store relevant information for future use. They evaluate their perspective by dividing the city into smaller areas and estimating the needs of each area within the New York City Data Application Database. Furthermore, they have shown that this system surpasses other predictive methods, such as future neural networks. In addition, they show how additional relevant information such as time, duration, and reduction affect the results. In the article by Yu et al. [29], a framework is proposed to suggest the needs of taxi passengers. They consider temporal, spatial, and external dependencies. The proposed deep learning framework integrates an updated density-based spatial clustering algorithm with noise and conditional generative adversarial network models. More specifically, the updated model is applied to the road network to create multiple subnetworks that consider the local relevance of taxi pick-up events. Comparative results show that the proposed model outperforms all other methods. It is recommended that more data be added to test future research models and that more information be added to improve prediction performance.

Taxi origin and destination flow forecasts for any city play an important role in passenger travel needs and taxi management and scheduling. However, complex local dependence and temporal mobility make this problem difficult. In the article by Duan et al. [30], a predictive model of a hybrid deep neural network based on convoluted LSTM was proposed. The underlying relationship between travel time and origin and destination flow was investigated to improve the prediction accuracy and integrated into the prediction model as input. Actual taxi data was used to fully validate the experiment's proposed model and forecasting system. Taxi demand forecasting is essential for making decisions on online taxi application platforms. The article by Zhang et al. [31] designed and explored how mutual variations can be used to improve grouping and area forecasting. First, a taxi zone grouping algorithm was developed based on the theory of grouping in pairs, which considers the relationships between the different taxi zones. Then, group-level and global prediction modules were developed to achieve internal and intercluster features, respectively. Finally, a multilevel recurrent neural network model was proposed to combine the two modules.

2.4. Electric Vehicle Charging Station Adoption. The construction of a charging station in the traffic network is a significant step toward the development of intelligent vehicle systems in urban areas [32–34]. Due to their high energy efficiency and low emissions, electric vehicles have become an attractive means of transportation to develop clean mobility systems. Infrastructure-based automation needs recharging facilities to meet the growing demand. The planning process is, of course, responsible for their impact on the power grid [35]. Chen et al. [36] first developed a new user balance model that described the distribution of road network balances along the charging lane. The battery recharge plan specified which charging lane to use, how long to charge, and which electric vehicle to drive. They developed charging lane applications under established user balance conditions as a math program with more complementary boundaries. The network balance and the design model were solved by efficient solution algorithms and illustrated with numerical examples. The Flow Refueling Location Model (FRLM) proposed by Kuby and Lim [37] is a flow interaction model that identifies locations on a network to maximize essential destination flow. Due to the limited driving distance of the vehicle, the network does not form a set of vertical dominance seats. The work by Miralinaghi et al. [38] provides a two-tiered mathematical model for understanding the decision-making process of transport companies and passengers. Under the structure, EV charge is a robust theoretical basis for network design. The design problem is solved using a functional set algorithm. The study results could serve as a guide for metropolitan transport companies to build capacity for specific locations and EVs, thus reducing long-term emissions. In another article by Miralinaghi et al. [39], they considered the problem of identifying charging stations in the transport network through mathematical programming. The proposed model applies to various alternative fuels and is particularly suitable for hydrogen fuels. They applied two well-known solution algorithms, branch-and-bound algorithm and Lagrangian relaxation algorithm, to solve the problem.

3. Methodology

We obtained the data from an electric kickboard provider, and then we used the k-means for clustering and bagging regressor for the final demand prediction. k-means clustering is a type of unsupervised learning [40]. k-means is used with 4 clusters. Bagging is a method of taking multiple samples and aggregating the results based on them, and each sample independently predicts the result [41]. The bagging regressor is used with three different models. Extreme Gradient Boosting (XGBoost), Extra Trees, and Random Forest are used for the base layer, and the Extra Trees model is used for the metalayer.

Extreme Gradient Boosting is a Gradient Boosting technique that reflects the weight of the result from the first sample to the following sample as opposed to bagging, where each sample independently predicts the result [42]. It continues to learn the weights of the results from the previous sample to affect the following sample as well. XGBoost has a faster learning rate and better model performance than other models based on Gradient Boosting. Gradient Boosting concentrates only on the training data results, and overfitting easily occurs. XGBoost can prevent overfitting by adjusting the hyperparameter values provided by the programmers by setting the desired learning method.

Random Forest is an algorithm that makes decisions through multiple decision trees, and it was created on the assumption that numerous ordinary algorithms solve problems better than one smart algorithm [43]. As a learning method, the final prediction value is determined by collecting the results determined by several trees. Random Forest is a representative bagging method and represents a voting method. Voting is a method of finally predicting the

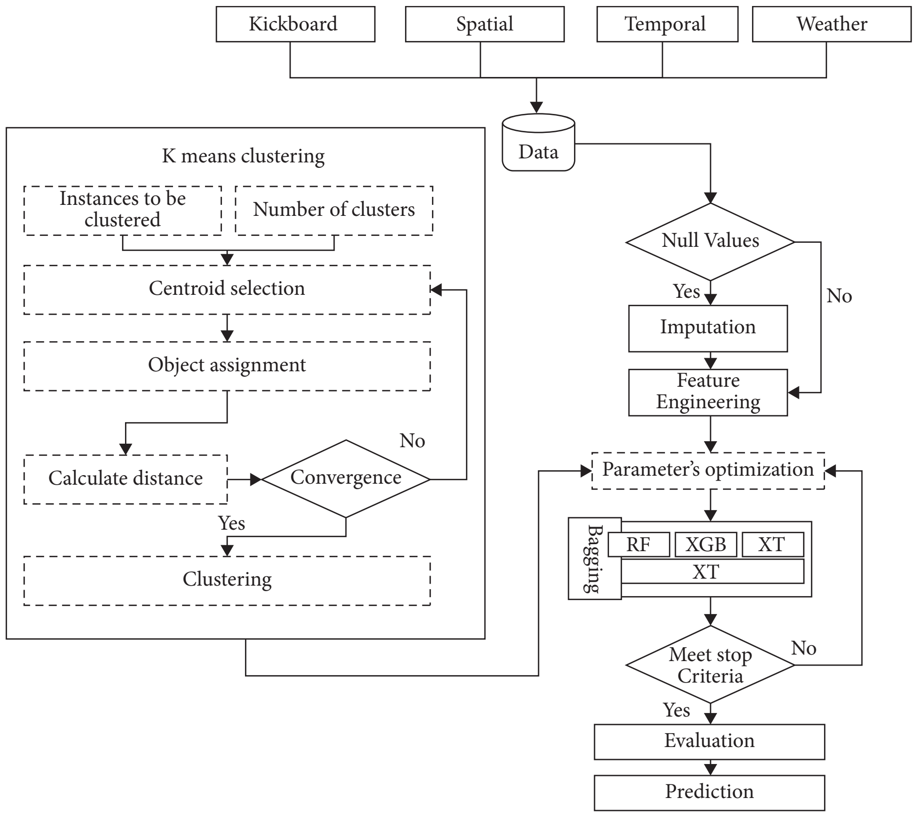

Figure 3: Flowchart of the proposed methodology.

highest value using the results of several samples [18]. Instead of using a single decision tree, learning is performed as many as the number of decision trees the programmer sets, and the results are collected. The most mentioned result is used as the final prediction value.

Extra Trees regressor learns in a similar way to Random Forest. However, Random Forest uses all feature values to produce results, whereas Extra Trees selects a method in which multiple decision trees randomly select features to produce optimal results [44]. Therefore, the learning speed of Extra Trees randomly selecting some features is faster than Random Forest using all feature values. Hence, we have used it as a metalearner.

Figure 3 shows the flow diagram of the proposed methodology. It starts with data aggregation. We combined the data from different sources such as kickboard, spatial, temporal, and weather data. Kickboard-related information consists of rent date, rent number, and sector information. Spatial information consisted of the x position and y position of the kickboard. Temporal information consisted of rent day, year, and month whereas weather data consisted of temperature, rain, humidity, and insolation. We checked whether there was any null value; if not, we performed feature engineering. If there were some null values, they were imputed using the mean. Feature engineering consisted of creating new features from existing parameters, such as extracting day, month, and week information from timestamps. The selected parameters were passed to the k-means clustering module where the instance was clustered, and the number of clusters was passed for centroid selection. We chose four clusters. The next step was to assign objects to the nearest distance and then calculate the distance. If convergence was achieved, then the final clustering step would be finished; otherwise, it would start again from centroid selection. The selected clusters were transferred for the optimal parameter selection. These optimal parameters were forwarded to the bagging regressor model, consisting of three base models and one metamodel. Random Forest, XGBoost, and Extra Trees regressor were used as base models, whereas Extra Trees was used as a metamodel to obtain the final prediction. The model was evaluated using different evaluation metrics such as R-squared, root mean square error, and Kolmogorov–Smirnov test, and then a prediction was made.

Figure 4 shows the structure of the proposed methodology. We have collected the electric kickboard data from the local kickboard company of Jeju Island, South Korea. Jeju Island is a famous island for tourism in South Korea. Tourists use electric kickboards to move from one place to another. We got the vehicle, spatial, and temporal information from them. Then, we got the weather information from Korea Metrological Department. We performed exploratory data analysis to understand the nature of the data. This data was preprocessed using different techniques, such as removing outliers and feature extraction. This preprocessed data was forwarded to the k-means clustering algorithm, where we found different clusters in Jeju Island. These clusters were passed to the bagging ensemble model

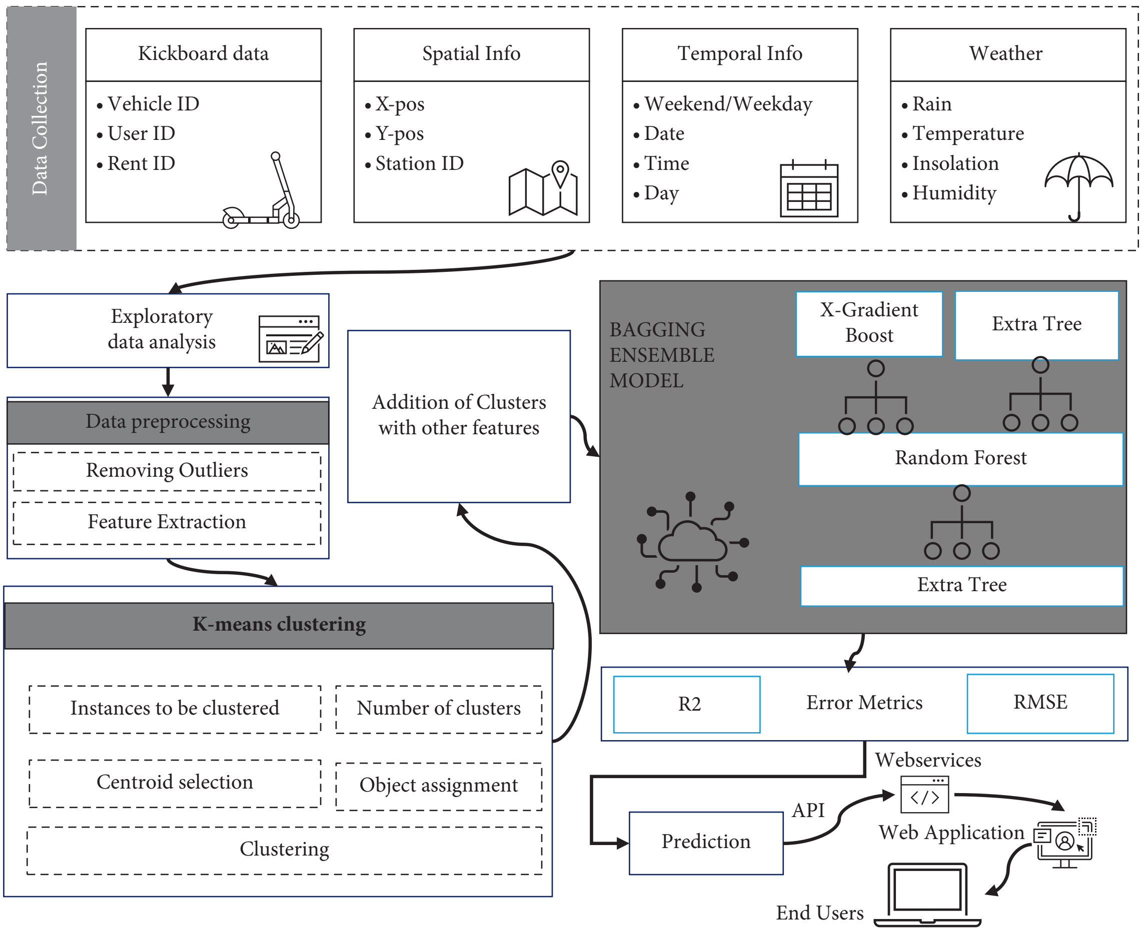

Figure 4: Structure of the proposed methodology.

and other spatiotemporal and vehicle features. This ensemble model consists of two layers [45]. Layer 0, or the base layer, consists of an Extreme Gradient Boosting, Random Forest, and Extra Trees model. Layer 1 or metalayer consists of an Extra Trees model. We used different evaluation metrics such as R-squared score and root means square error (RMSE) to evaluate our proposed approach. The final prediction was forwarded to the web application using web services. End users could see the future prediction about electric kickboard demand for specific locations.

4. Data Analysis

In recent years, the electric scooter, kickboards, and bikes in many cities across the world have provided an excellent opportunity to reduce short-distance driving [46]. The data used for the study was the demand data of electric mobility (electric kickboard) service company that started services on Jeju Island in April 2019. Data from EV Pass company, a company that provides electric mobility services on Jeju Island, was used. The total number of data instances is service users' number of use cases during the data collection period. The collection period is 717 days, from April 16, 2019, to June 11, 2021. This study predicts the daily demand for electric mobility by grouping the demand for electric mobility by day. In addition, we imported weather data from the Korea Meteorological Administration [47] and added external factors that affect the use of electric mobility, such as daily average temperature and precipitation, and dividing weekends and weekdays.

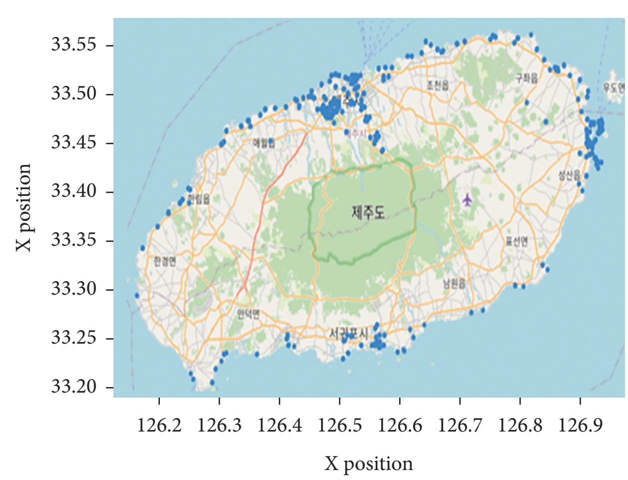

Figure 5: Rental location according to latitude and longitude.

Figure 5 shows rental locations according to latitude and longitude. The x-axis represents the x position or latitude, and the y-axis shows the y position or longitude.

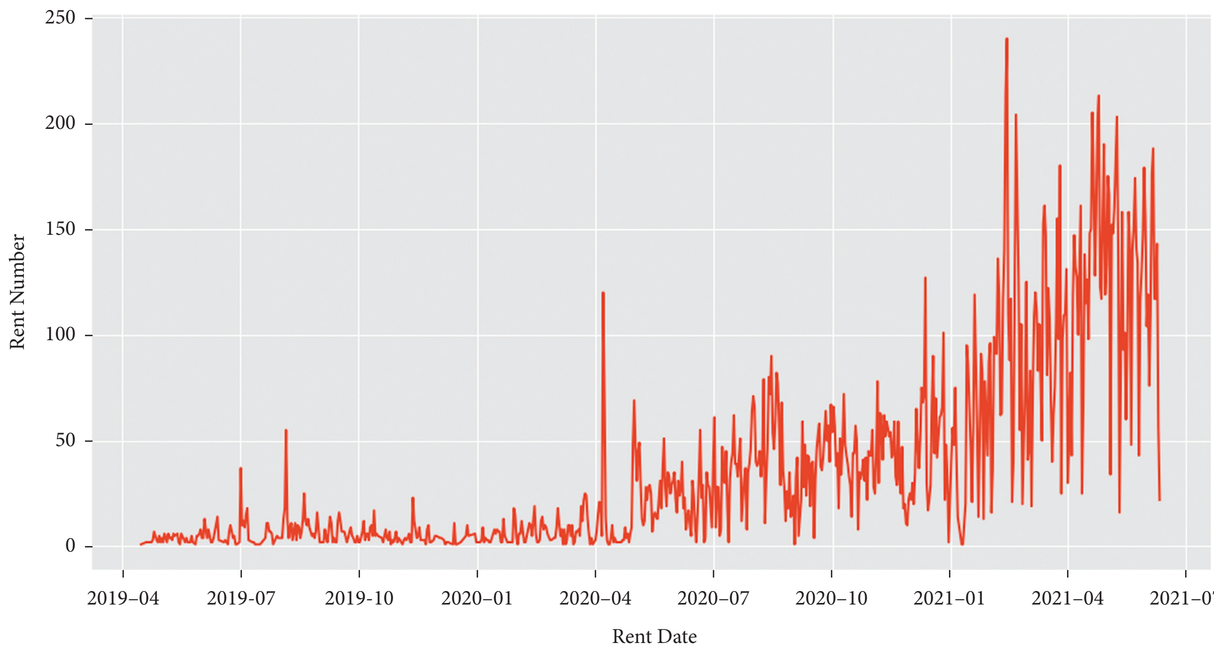

Figure 6: Daily demand for electric kickboards.

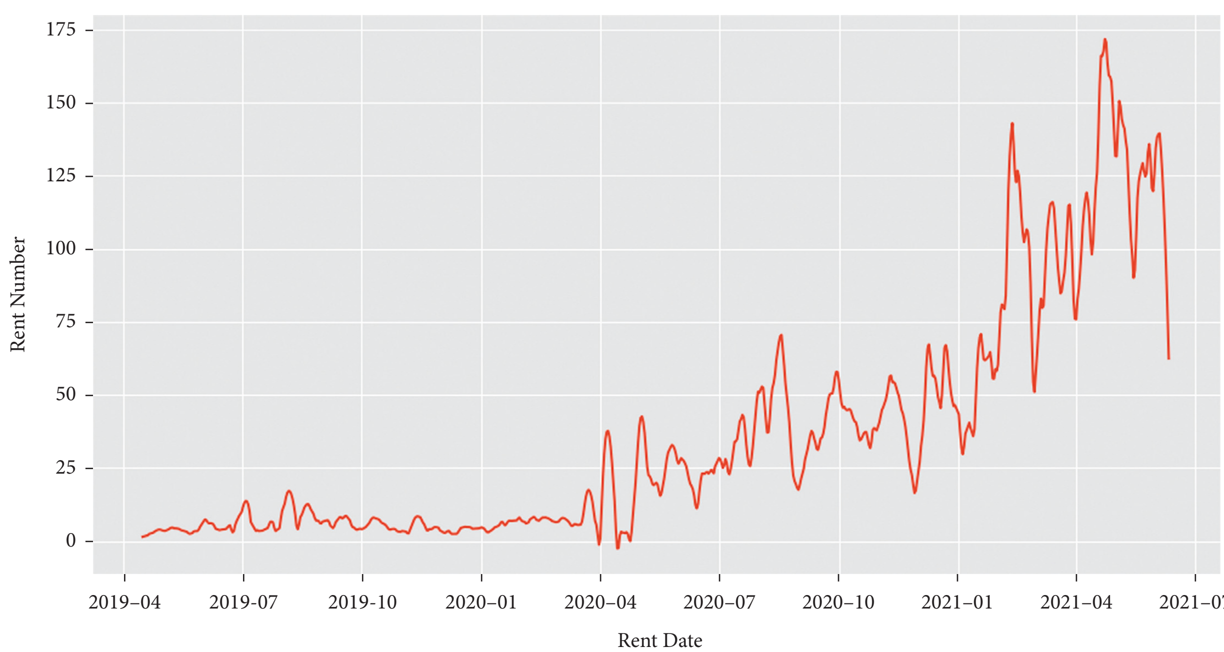

Figure 7: Daily demand for electric kickboards after smoothing the data.

Figure 6 shows daily demand for electric kickboards. The *x*-axis represents the date, and the *y-axis* represents the total daily demand for that day. Demand, which was low at the beginning of the service, increased after a certain period of time. This can be thought of as a demand phenomenon for startups in general. In addition, demand was not constant and showed large differences from day to day. This study was conducted by stabilizing these unstable data through smoothing. The window size for data smoothing was set to 11, and the window size standardizes the data by grouping the day and the days before and after it. The window size of 11 means the midday and five days before and after, and Figure 7 shows the data smoothing result.

Figure 8 explains the effect of the holiday, weekend, and weekday on rental kickboard demand. The *x*-axis represents the feature name, and the *y*-axis shows the average rent

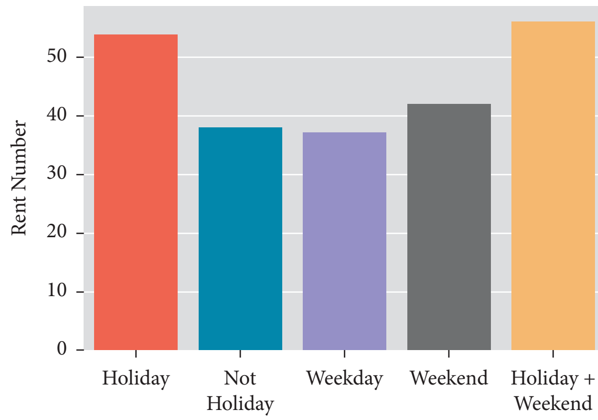

FIGURE 8: Effect of the holiday, weekend, and weekday on rental kickboard demand.

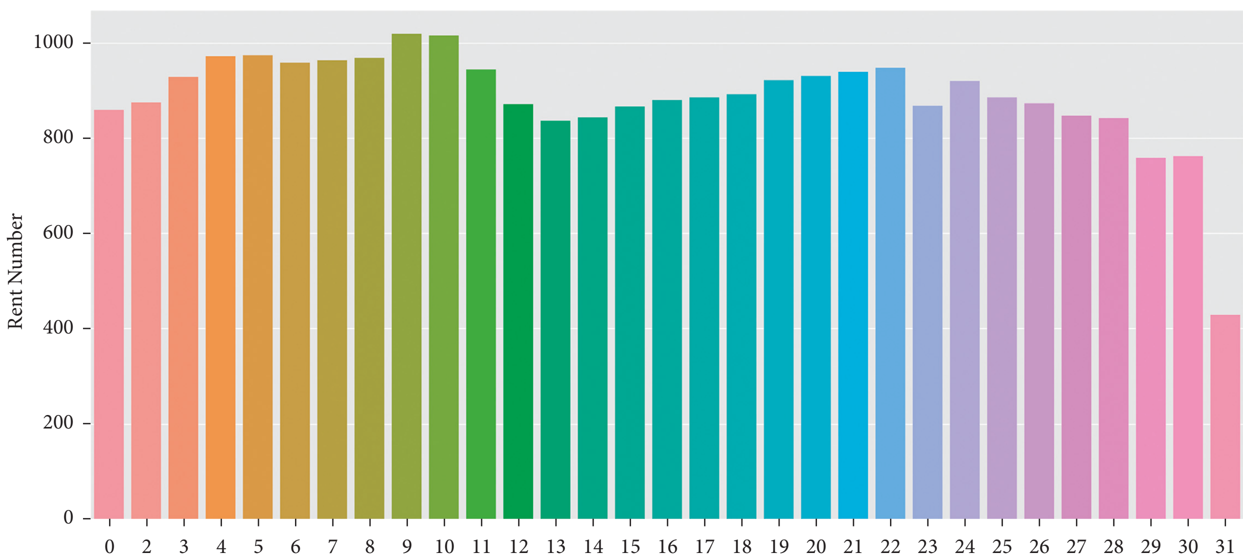

FIGURE 9: Total Demand on each day of a month.

TABLE 2: Simulation environment.

Sr#	Property	Specification
1	Programming language	Python 3.7.6
2	Operating system	Ubuntu 18.04
3	Browser	Google Chrome
4	Framework	Jupyter Notebook
5	CPU	Intel Core i7 CPU @ 1.80 GHZ
6	Memory	16 GB
7	Graphic card	Radeon 540

number for that day. The holiday accounts for the most rental kickboards, whereas weekdays account for the least numbers if there is a holiday and weekend with the maximum number of rental kickboards.

Figure 9 explains demand on each day of a month. The x-axis represents the day number of the month, and the y-axis shows the total rent number on that specific day.

5. Results

This section covers the experimental results achieved using our presented approach. We have also compared our presented model with state-of-the-art algorithms. We have used the Jupyter notebook on Ubuntu 18.04 for coding in Python 3.7.6. Table 2 summarize the simulation environment used

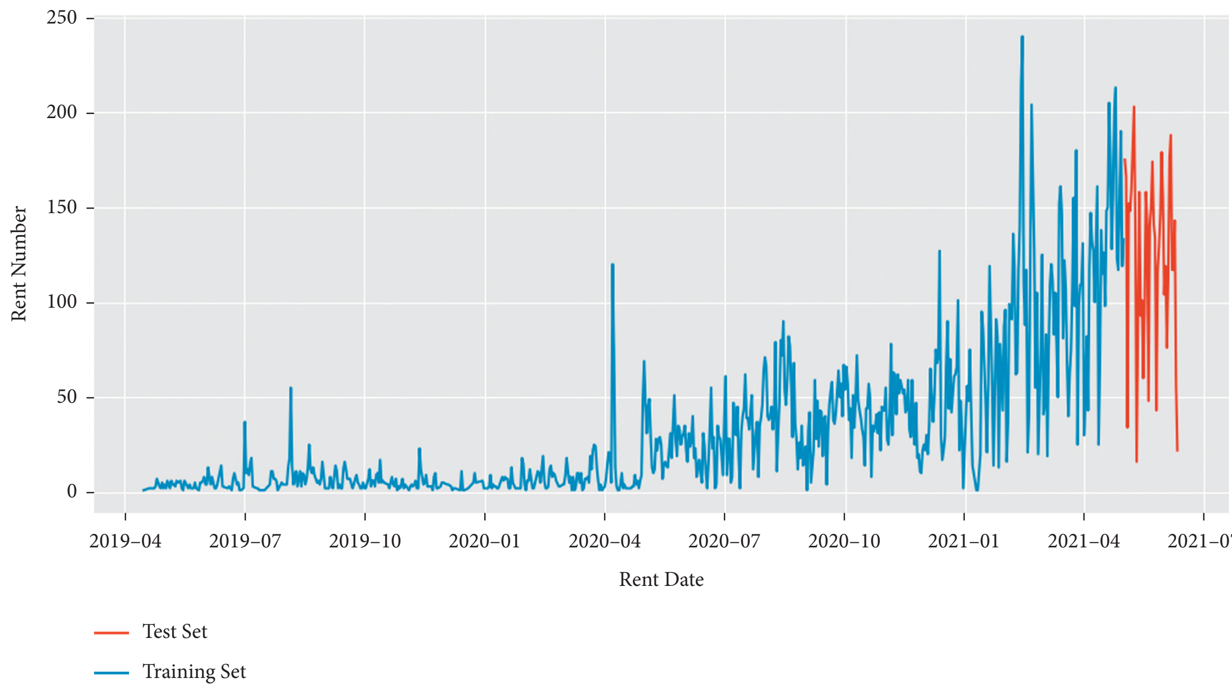

FIGURE 10: Training and testing data distribution.

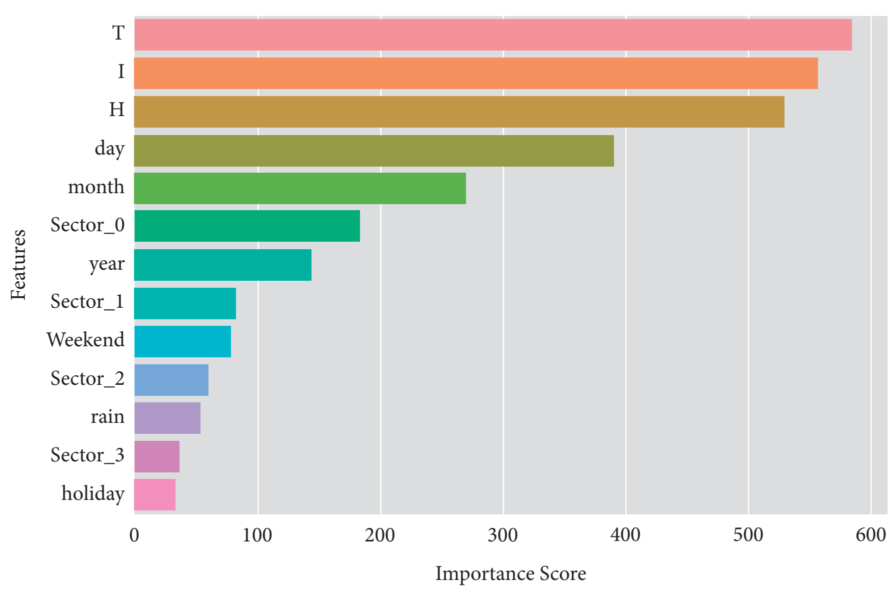

FIGURE 11: Feature importance graph.

for this research. We have used 80 percent of data for model training and 20 percent for result validation. Figure 10 reflects the training and test data distribution. The x-axis represents the date, and the y-axis shows the rent count. The blue line shows the training set, and the black line shows the testing dataset.

Feature importance is also commonly referred to as the feature selection method. When supervised learning makes predictions through learned data, it is a numerical expression of the effect of each feature on the result. In the time series data sorted by day, the feature importance was higher as the feature had a clear pattern and subdivided numerical values among the information representing each day. Figure 11 depicts feature importance graph. T represents temperature, I represents insulation, and H represents humidity. Sector 0 is the first sector, and sector 3 is the fourth sector. Other features are day, month, year, weekend, rain, and holiday. It is observed that temperature, insulation, and humidity impact the final prediction. The x-axis represents the feature importance score, and the y-axis shows the name

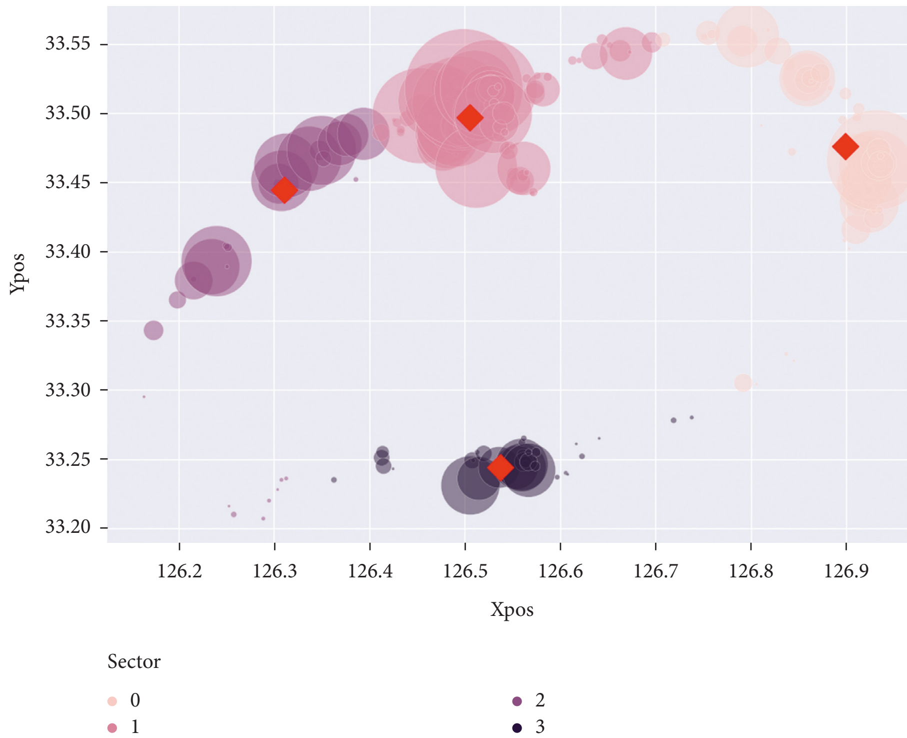

Figure 12: Clustering with four sectors.

of the features. The feature importance is calculated using the importance score where temperature, insulation, and humidity have more importance than rain in the final prediction.

In segmenting regions, the division results based on latitude and longitude are also compared with the results of clustering division using the k-means algorithm. Figure 12 displays clustering with 4 clusters. Apply k-means clustering with 4 clusters. Red spots represent the centroid of the cluster. Sectors are numbered 0, 1, 2, and 3. The x-axis represents the x position or latitude, and the y-axis shows the y position or longitude.

Figure 13 explains sector-wise demand, where sector 1 is the hotspot for rental kickboards and sector 3 has minimum kickboard demand. Sector 1 represents the Jeju-si district, and sector 3 represents the Seogwipo-si district. The population of Jeju-si is around 492 thousand, while that of Seogwipo-si is 179 thousand. Moreover, the total population of Jeju-si stands at around 671 thousand [48]. The difference in population is also a reason for more demand in sector 1. The x-axis represents the sector number, and the y-axis shows the total rent number in that specific sector. The figure shows the difference in the size of the dots according to the total number of rentals at each rental office on Jeju Island during the data collection period. It can be seen that the number of electric mobility rentals near Jeju Airport and famous tourist destinations such as Aewol and Seongsan is generally large. The demand for electric scooters is usually high at tourist attractions. Jeju Island consists of many tourist attractions such as Hallasan Mountain Natural Reserve, Geomunoreum Lava Tube System, and Seongsan Ilchulbong Tuff Cone.

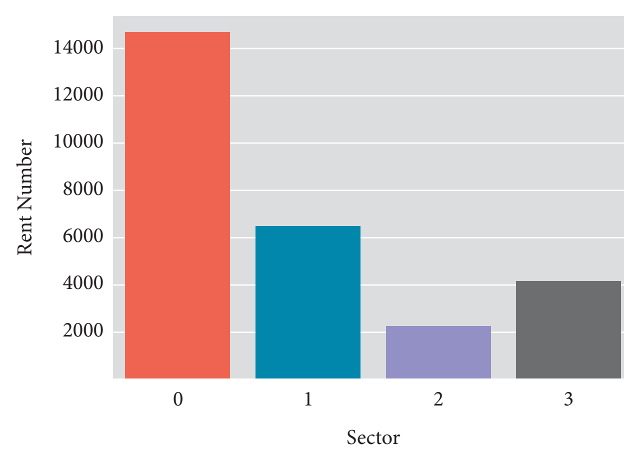

Figure 13: Sector-wise demand.

Figure 14 shows prediction results. The light blue line shows the actual value, and the black line shows the predicted value. This graph shows the result of the proposed approach for the test data. We have used test data from May 1, 2021, to June 11, 2021. The x-axis represents the date, and the y-axis shows the rent count.

Root mean square error (RMSE) is defined as the square root of mean square error (MSE) [49]. It is used to measure the difference from the actual values of the predicted values. The formula for calculating RMSE is given in (1), where n is the total number of observations, y_{ob} represents the

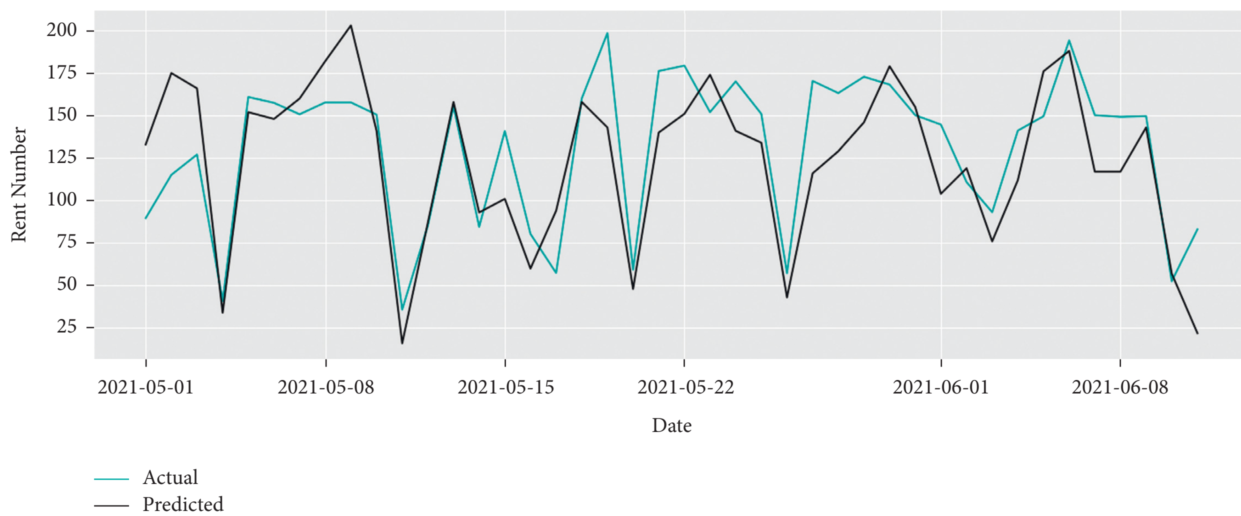

FIGURE 14: Prediction result of the proposed approach.

TABLE 3: Comparison of the proposed approach with different individual models.

Sr#	Model	R^2 score	RMSE
1	CatBoost	78.21	46.78
2	Extra Trees	91.67	21.23
3	XGBoost	89.64	29.91
4	LGBM	84.48	36.68
5	Random Forest	87.12	27.61
6	Gradient Boosting	68.17	39.31
7	Proposed	93.42	24.6

TABLE 4: Comparison of the proposed approach with different combinations.

Hybrid model combinations		R^2 score
Base layer	Metalayer	
CatBoost + Extra Trees + LGBM	CatBoost	67.67
CatBoost + Extra Trees + Random Forest	Extra Trees	72.57
CatBoost + Extra Trees + XGBoost	XGBoost	70.47
CatBoost + LGBM + Random Forest	Random Forest	79.24
Extra Trees + XGBoost + Random Forest	Random Forest	87.32
Extra Trees + XGBoost + Random Forest	XGBoost	89.05
Extra Trees + XGBoost + Random Forest	Extra Trees	93.42

observed actual value, and y_{es} represents the estimated (predicted) value. We have achieved an RMSE of 24.67 using our proposed approach. Table 3 shows a comparison of the proposed approach with different individual models.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(y_{ob} - y_{es}\right)^2}{n}}. \quad (1)$$

The R^2 score or regression score is a statistical measure that is defined as a set coefficients that involves observed and predicted values [50]. A regression score is used to estimate how well the reaction model works. R^2 is an indication of the good performance achieved by the reaction model if it is near score 1 and bad performance if the value is near to zero.

The R^2 score is calculated based on (2), where n is the total number of observations, y_{ob} represents the observed actual value, and y_{es} represents the estimated (predicted) value.

$$R^2 \text{ score} = 1 - \frac{\sum\left(y_{ob} - y_{es}\right)^2}{\sum\left(y_{ob} - \overline{y}_{es}\right)^2}. \quad (2)$$

We have achieved R^2 of 93.42 using our proposed approach. We have compared our model with different other combinations of bagging regressors, as shown in Table 4 which displays the models used in the base layer and the metalayer.

The Kolmogorov–Smirnov goodness of fit test (K–S test) compares the data with a known distribution and shows if

Table 5: Kolmogorov–Smirnov goodness of fit test.

Feature	Statistics	P value
Sector 1	0.052	1.00
Sector 2	0.091	0.68
Sector 3	0.119	0.44
Sector 4	0.013	1.00

they have the same distribution. We performed the K–S test on our four sectors. The results of the K–S test are represented in Table 5.

The key element in the proposed model is the bagging ensemble method. This method allows one to take advantage of different models and combine them into one model. Another critical step proposed in this article is to cluster the demand according to regions—this helps improve the accuracy. The major drawback of other forecasting models that result in less accurate forecasting is the lack of ensemble technique.

6. Conclusions

The demand for electric mobility is increasing, especially in tourist attractions. Machine learning can help accurately predict the electric mobility demand in areas where companies struggle to meet the demand at the proper location. This article performs classification-aided bagging regressor prediction of supervised learning using a small amount of data and unstable data with a significant difference in demand. We have used the data from a local electric kickboard provider on Jeju Island, South Korea. The company provides electric kickboards for rent to tourists and residents. Data smoothing stabilized the irregular pattern between data while maintaining the overall demand pattern. Data with similar characteristics were grouped using clustering, and data with different characteristics were separated to predict demand. We have utilized the k-means algorithm for clustering and bagging ensemble model for final prediction. The bagging ensemble model consists of XGBoost, Extra Trees, and Random Forest algorithms. We have used an Extra Trees model as a metalearner for the proposed model. Through this, the forecasting results significantly increased, and the demand forecasting accuracy results after the regional division of Jeju Island were also enhanced. We have achieved R^2 of 93.42 using our proposed approach. The results of this study can be helpful for the electric mobility providers who want to predict the demand at a specific city location accurately. In the future, genetic algorithm can be used for feature optimization and hyperparameter optimization.

Abbreviations

ML:	Machine learning
LSTM:	Long short-term memory
GARCH:	Generalized autoregressive conditional heteroskedasticity
SARIMA:	Seasonal autoregressive moving average
BDSTN:	Bidirectional deep spatial-temporal network
HDBSCAN:	Hierarchical density-based spatial clustering of applications with noise
H-ConvLSTM:	Hexagonal convolution operation LSTM
DSTGNN:	Dynamic spatiotemporal graph neural networks
GHG:	Greenhouse gas emissions
EV:	Electric vehicle
XGboost:	Extreme gradient boost
RMSE:	Root mean square error
K-S Test:	Kolmogorov-smirnov test

Data Availability

The data used to support this study are available from the corresponding authors upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Research Article

Robust Tracking Control of a Three-Phase Bidirectional Charger for Electric Vehicle

Chivon Choeung[1,2] **Meng Leang Kry**[3] **and Young-Il Lee**[4]

[1]*Faculty of Electricity, National Polytechnic Institute of Cambodia, Phnom Penh, Cambodia*
[2]*Graduate School, National Polytechnic Institute of Cambodia, Phnom Penh, Cambodia*
[3]*Business and Transmission Department, Electricity of Cambodia, Phnom Penh, Cambodia*
[4]*Department of Electrical and Information Engineering, Seoul National University of Science and Technology, Seoul, Republic of Korea*

Correspondence should be addressed to Chivon Choeung; choeungchivon@npic.edu.kh

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This paper presents a robust control strategy for an electric vehicle's three-phase off-board bidirectional AC-DC battery charger. The conventional constant current (CC) and constant voltage (CV) charging mode are considered to provide a fast-charging performance for the batteries. The bidirectional charger also allows using of the vehicle as an energy storage system for the grid i.e., charging during the peak-off times and delivering the energy back to the grid during peak times of electrical consumption. In discharging mode, the bidirectional charger maintains constant active power flow to the grid with a given reference. For both cases, user of a robust state feedback controller with integral action is made in the *DQ*-synchronous frame. The set of stabilizing gains of this controller are determined by a linear matrix inequality (LMI)-based optimization so that the convergence time to steady stead is minimized in the occurrence of the parametric uncertainties of the L-filter. The efficacy of the proposed controller is verified through simulation and experimental results on 102.4 V Lithium iron phosphate ($LiFePO_4$) batteries.

1. Introduction

With a tremendous demand for renewable energy throughout the world, sustainable transportation methods draw a lot of attention in comparison to conventional transportation [1]. An enormous number of electric vehicles (EV) and plug-in hybrid electric vehicles (PHEV) are currently being utilized due to their eco-friendly behavior. For that reason, researchers, governments, and automakers worldwide continue to pursue efforts through policy and design to increase the EV market share. Many control techniques have been proposed to answer to the demands of rapid charging and energy-efficient battery charger.

In [1, 2] conventional proportional integral (PI) control has been studied for single-phase bidirectional chargers. These methods were proposed using a constant-current (CC) and a constant-voltage charging stage that produce faster-charging capability than that of only fixed voltage charging methods. The topology of these methods is single-phase based, so the amount of charging current of these chargers is less than those of the three-phase topology. Moreover, another main drawback of the PI controller of [1, 2] is to gain tuning efforts for both inner-loop and outer-loop controllers.

A bidirectional three-phase charger has been proposed using model predictive control [3]. This scheme provides a bidirectional power transfer with instantaneous mode charging capability and fast dynamic response. However, due to its only one charging stage (CV) from the grid to a vehicle (G2V), the batteries need more time to be fully charged. This method also requires a high computational power which results in high sampling frequency. Moreover, without integration of an integral control or a disturbance observer, this method may result in output offset-state error.

Deadbeat control has been presented in [4] for the DC-DC part of the bidirectional charger to regulate the charging current to the battery while PI control is also used for the AC-DC converter side to maintain the DC-link voltage constant. It is known that deadbeat control produces fast transient performance in which settling time reaches the steady state in just a few sampling periods. This control method is sensitive to system uncertainty and measurement noise, particularly for high sampling frequency.

The topology of [1, 2], and [4] consist of a DC-DC converter for the CC/CV charging stage and an AC-DC converter for power factor and DC-link voltage control. In [5, 6], DC-DC converters have been used for single-phase chargers and [7, 8] for the three-phase charger to improve charging efficiency. Three operations of bidirectional chargers such as grid-to-vehicle (G2V), vehicle-to-grid (V2G), and vehicle-to-home (V2H) were considered in [5, 8] to provide a full charging capability of bidirectional charger for an electric vehicle. Yet, classical controllers such as PI and PR were adopted which results in multiloop gain tuning.

Taking battery lifespan into account, AI-based manufacturing and management have been reviewed in [9]. This review provides a systematic survey of AI-based manufacturing and management solutions for enhancing battery health performance with a focus on recent challenges and opportunities. Data science-based full-lifespan management strategies have also been discussed in [10] to furnish useful reference points to support the design of data science-based battery management solutions during its lifespan, while a brand-new hologram to make full use of battery during full-lifespan will be formulated.

In the case of advanced control methods, battery temperature is considered a key part of the battery thermal management for battery operation safety and behavior. In [11], a constrained generalized predictive control was proposed based on a newly developed coupled thermoelectric model. This method can be easily implemented in other battery charging applications to control the charge current and guarantee charging efficiency with a long lifespan. A leader-follower-based approach has been discussed in [12] to enable optimal charging control for the Li-ion battery pack. This method is capable of reducing the computational burden and enhancing the robustness to minimize the negative impact of the cells' model bias.

In this paper, a robust tracking control of a three-phase bidirectional charger is presented for electric vehicle applications without using a DC-DC converter as an interface between a three-phase AC-DC converter and batteries. The LMI-based robust tracking control is a well-known method and has been proposed for three-phase inverters [13, 14] and three-phase chargers [15, 16]. This proposed bidirectional charger is capable of charging Tesla Model S batteries which range between 352 V and 402 V. The battery is charged with a constant current until the voltage reaches the recommended maximum voltage, then the voltage is maintained constant until the current consumed by the battery falls to a residual value. During the discharging operation mode, the energy stored in the batteries can be delivered back to the power grid. The vehicle-to-grid (V2G) technology is crucial from the viewpoint of the European Union and the bidirectional charger allows to use of the Full Electric Vehicle as an energy storage system for the electric grid, charging them in the peak-off times and delivering the energy back to the grid in peak times of electrical consume. For both cases, the use of a robust state feedback controller with integral action is made in the *DQ*-synchronous frame to provide stability and eliminate the steady-state error. Unlike a conventional MPC, this proposed controller is capable of removing an offset error to provide a good reference tracking output. This method also provides a systematic controller design by reducing the effort of gain tuning compared to the conventional PI controller and guaranteeing stabilized performance under parameter uncertainty. The set of stabilizing gains of this controller are determined by a linear matrix inequality (LMI)-based optimization so that the convergence time to steady stead is minimized in the occurrence of the parametric uncertainties of the L-filter. The consideration of an uncertainty model in this proposed method provides a wider range of good performance under the uncertain value of the L-filter than a deadbeat control. In the case of charging control, an outer-loop PI controller is employed to maintain the dc-current and dc-voltage for CC and CV control, respectively. The conventional phase-locked loop (PLL) is considered in this paper to obtain grid voltage phase angle.

2. System Description

A three-phase bidirectional charger circuit is shown in Figure 1. The dynamic of the line current is expressed in the *abc*-axis as follows:

$$\begin{cases} L\dfrac{di_a(t)}{dt} + Ri_a(t) &= E_m \sin(\omega t) - v_{a,i} \\ L\dfrac{di_b(t)}{dt} + Ri_b(t) &= E_m \sin\left(\omega t - \dfrac{2\pi}{3}\right) - v_{b,i}, \\ L\dfrac{di_c(t)}{dt} + Ri_c(t) &= E_m \sin\left(\omega t - \dfrac{4\pi}{3}\right) - v_{c,i} \end{cases} \quad (1)$$

where

$$v_{a,i} := \frac{2u_a - u_b - u_c}{6v_o(t)},$$

$$v_{b,i} := \frac{-u_a + 2u_b - u_c}{6v_o(t)},$$

$$v_{c,i} := \frac{-u_a - u_b + 2u_c}{6v_o(t)}.$$

$$\text{Here,} \begin{cases} 1, & S_x = \text{on}; \quad \overline{S}_x = \text{off}; \\ -1, & S_x = \text{off}; \quad \overline{S}_x = \text{on}; \end{cases} \quad u_x\,(x = a, b, c). \quad (2)$$

The dynamic in *abc*-axis (1) can be transformed into the *dq*-axis as follows [17]:

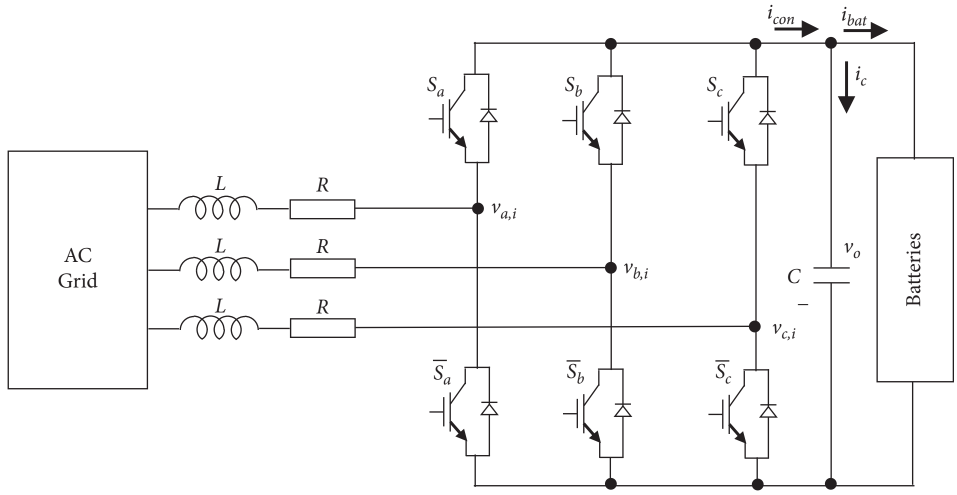


Figure 1: Three-phase bidirectional charger with L-filter.

$$\frac{d\mathbf{i}_{dq}(t)}{dt} = \mathbf{A}_c\mathbf{i}_{dq}(t) + \mathbf{B}_c v_o(t)\mathbf{u}(t) + \mathbf{d}_c(t), \tag{3}$$

where $\mathbf{i}_{dq}(t) := \begin{bmatrix} i_d(t) \\ i_q(t) \end{bmatrix}$, $\mathbf{u}(t) = \begin{bmatrix} u_d(t) \\ u_q(t) \end{bmatrix}$, $\mathbf{d}_c(t) = \begin{bmatrix} 0 \\ -E_m/L \end{bmatrix}$, $\mathbf{A}_c = \begin{bmatrix} -R/L & \omega \\ \omega & -R/L \end{bmatrix}$, $\mathbf{B}_c = \begin{bmatrix} -1/2L & 0 \\ 0 & -1/2L \end{bmatrix}$

ω is the angular frequency of the AC voltage source. The inductor current $\mathbf{i}_{dq}(t)$ and the control input $\mathbf{u}(t)$ in the dq-frame satisfy the relationship as follows:

$$\begin{aligned} \mathbf{i}_{dq}(t) &= \frac{2}{3}\mathbf{T}(t)\mathbf{i}_{abc}(t), \mathbf{i}_{abc}(t) = \frac{3}{2}\mathbf{T}^T(t)\mathbf{i}_{dq}(t), \\ \mathbf{u}(t) &= \frac{2}{3}\mathbf{T}(t)\mathbf{u}_{abc}(t), \mathbf{u}_{abc}(t) = \frac{3}{2}\mathbf{T}^T(t)\mathbf{u}(t), \end{aligned} \tag{4}$$

where $\mathbf{T}(t) := \begin{bmatrix} \cos(\omega t) & \cos(\omega t + 2\pi/3) & \cos(\omega t + 2\pi/3) \\ -\sin(\omega t) & -\sin(\omega t + 2\pi/3) & -\sin(\omega t + 2\pi/3) \end{bmatrix}$,

$$\mathbf{T}^T(t) := \begin{bmatrix} \cos(\omega t) & -\sin(\omega t) \\ \cos\left(\omega t - \frac{2\pi}{3}\right) & -\sin\left(\omega t - \frac{2\pi}{3}\right) \\ \cos\left(\omega t - \frac{2\pi}{3}\right) & -\sin\left(\omega t - \frac{2\pi}{3}\right) \end{bmatrix}. \tag{5}$$

On the other hand, the output voltage $v_o(t)$ in the state equation (2) is governed by the following dynamic:

$$C\frac{\mathrm{d}v_o(t)}{\mathrm{d}t} = i_{\mathrm{con.}}(t) - i_{\mathrm{bat.}}(t), \tag{6}$$

where

$$i_{\mathrm{con.}}(t) = \frac{3}{4}\mathbf{i}_{dq}^T(t)\mathbf{u}(t). \tag{7}$$

where $i_{con.}$ is the converter current and $i_{\mathrm{bat.}}$ is an output current to the battery.

The control input variable $\mathbf{u}(t) := \begin{bmatrix} u_d(t) & u_q(t) \end{bmatrix}^T$ must be constrained as follows [18]:

$$\|\mathbf{u}(t)\| \le \frac{2}{\sqrt{3}}. \tag{8}$$

The dynamic (2) can be transformed in the following discrete time with sampling period h [19] as follows:

$$\mathbf{x}(k+1) = \mathbf{A}_d\mathbf{x}(k) + \mathbf{B}_d v_o(t)\mathbf{u}(k) + \mathbf{d}(k), \tag{9}$$

where $\mathbf{x}(k) := [i_d(k)/i_q(k)]$, $\mathbf{A}_d = e^{\mathbf{A}_c h} = e^{-\alpha h}\begin{bmatrix} \cos(\omega h) & \sin(\omega h) \\ -\sin(\omega h) & \cos(\omega h) \end{bmatrix}$, $\mathbf{d} = (\int_0^h e^{\mathbf{A}_c t}dt)\mathbf{d}_c = E_m/L\begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$, $\mathbf{B}_d = (\int_0^h e^{\mathbf{A}_c t}dt)\mathbf{B}_c = 1/2L\begin{bmatrix} b_1 & b_2 \\ -b_2 & b_1 \end{bmatrix}$, $\alpha := R/L$.

$$\begin{aligned} b_1 &:= \frac{\alpha - e^{-\alpha h}(\alpha\cos(\omega h) - \omega\sin(\omega h))}{\alpha^2 + \omega^2}, \\ b_2 &:= \frac{\omega - e^{-\alpha h}(\omega\cos(\omega h) + \alpha\sin(\omega h))}{\alpha^2 + \omega^2}. \end{aligned} \tag{10}$$

3. Model Uncertainties and Offset-free Control

In this section, the uncertainties model of the system and offset-free control are discussed. Suppose that the value of L and R in each phase are equal but vary in certain ranges below as follows:

$$L_{\min} \le L \le L_{\max}, \tag{11a}$$

$$R_{\min} \le R \le R_{\max}. \tag{11b}$$

Here, we denote the matrices $(\mathbf{A}_d, \mathbf{B}_d)$ corresponding to the four possible combinations of the immoderate value of $1/L$ and $1/R$ as $(\mathbf{A}_i, \mathbf{B}_i)$ $(i = 1,2,3,4)$ and suppose that the matrices $(\mathbf{A}_d, \mathbf{B}_d)$ belong to the polytopic uncertain set $\mathbf{\Psi}$ below as follows:

$$\mathbf{\Psi} = \left\{ \sum_{n=1}^{4}\mu_n(\mathbf{A}_i, \mathbf{B}_i) | \sum_{n=1}^{4}\mu_n = 1, \mu_n \ge 0 \right\}. \tag{12}$$

The uncertainties of the system can be any kind of variation but should lie within the range (9). The system uncertain range can be determined as follows:

$$L_0/\mu \le L \le \mu L_0, \tag{13a}$$

$$R_0/\mu \le R \le \mu R_0, \tag{13b}$$

where R_0 and L_0 are the nominal value of the filter resistance and inductance, respectively, and μ (>1) can be considered as a tuning parameter.

To compensate for the offset error despite the system's uncertainty model, the control law based on [10] is employed for (8)as follows:

$$\begin{cases} \mathbf{w}(k) = \mathbf{w}(k+1) + (\mathbf{x}_{\mathrm{ref}} - \mathbf{x}(k-1)) \\ \mathbf{u}(k) = \mathbf{K}\mathbf{x}(k) + \mathbf{L}\mathbf{w}(k) \end{cases}, \tag{14}$$

where $\mathbf{K}$ and $\mathbf{L}$ are state feedback and integrator gains, respectively. Because of the integrator in (12), the steady-state error between the reference state $\mathbf{x}_{ref}$ and the grid-current $\mathbf{x}$ will be compensated provided that the closed-loop system is stable. The reference state $\mathbf{x}_{\mathrm{ref}} := \begin{bmatrix} i_{\mathrm{d}}^{\mathrm{ref}} & i_q^{\mathrm{ref}} \end{bmatrix}^T$ is generated by the outer-loop controller in the case of charging mode and can be computed with a given power reference in the case of discharging stage.

4. Robust Optimal Gain

Here, let us determine the gains of (12) so that the closed-loop stability is provided to the system in the occurrence of parametric uncertainties. A systematic design method is proposed to obtain stabilizing state feedback gain $\mathbf{K}$ and integral gain $\mathbf{L}$ using LMI. From relations (8) and (12), we get the following:

$$\begin{bmatrix} \mathbf{x}(k+1) \\ \mathbf{w}(k+1) \end{bmatrix} = \begin{bmatrix} \mathbf{A}_d & 0_{2\times 2} \\ -\mathbf{C} & \mathbf{I}_{2\times 2} \end{bmatrix} \begin{bmatrix} \mathbf{x}(k) \\ \mathbf{w}(k) \end{bmatrix} + \begin{bmatrix} \mathbf{B}_d \\ 0_{2\times 1} \end{bmatrix} \mathbf{u}(k) + \begin{bmatrix} \mathbf{d}(k) \\ \mathbf{x}_{ref} \end{bmatrix}. \tag{15}$$

where output matrix $\mathbf{C} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. Relation (13) can be simplified as follows:

$$\overline{x}(k+1) = \mathbf{A}_u \overline{x}(k) + \mathbf{B}_u \mathbf{u}(k) + \mathbf{D}(k), \tag{16}$$

where $\overline{x}(k) := \begin{bmatrix} \mathbf{x}(k) \\ \mathbf{w}(k) \end{bmatrix}$, $\mathbf{A}_u := \begin{bmatrix} \mathbf{A}_u & 0_{2\times 2} \\ -\mathbf{C} & \mathbf{I}_{2\times 2} \end{bmatrix}$, $\mathbf{B}_u := \begin{bmatrix} \mathbf{B}_d \\ 0_{2\times 2} \end{bmatrix}$, $\mathbf{D}(k) := \begin{bmatrix} \mathbf{d}(k) \\ \mathbf{x}_{ref} \end{bmatrix}$.

The control input $\mathbf{u}(k)$ can be given as follows:

$$\mathbf{u}(k) = \mathbf{F}\overline{x}(k)\mathbf{F} := \begin{bmatrix} \mathbf{K} & \mathbf{L} \end{bmatrix}. \tag{17}$$

Suppose that $\mathbf{D}\ (k) = 0$ to determine stabilizing gain $\mathbf{F}$, then the closed-loop system can be computed as follows:

$$\overline{x}(k+1) = (\mathbf{A}_u + \mathbf{B}_u \mathbf{F})\overline{x}(k). \tag{18}$$

The closed-loop system (16) is stable [20] if there exists a positive-definite matrix $\mathbf{W}$ such that

$$\mathbf{W} - (\mathbf{A}_u + \mathbf{B}_u \mathbf{F})^T \mathbf{W} (\mathbf{A}_u + \mathbf{B}_u \mathbf{F}) > 0. \tag{19}$$

It can be seen that the condition (17) holds for some $\mathbf{W}_0 > 0\,(\mathbf{W}_0 < \mathbf{W})$

$$\mathbf{W}_0 - (\mathbf{A}_u + \mathbf{B}_u \mathbf{F})^T\, \mathbf{W} (\mathbf{A}_u + \mathbf{B}_u \mathbf{F}) > 0. \tag{20}$$

By employing Schur complement [20] to (18), we get

$$\begin{bmatrix} \mathbf{S}_0 & (\mathbf{A}_u \mathbf{S}_0 + \mathbf{B}_u \mathbf{H})^T \\ \mathbf{A}_u \mathbf{S}_0 + \mathbf{B}_u \mathbf{H} & \mathbf{S} \end{bmatrix} > 0, \tag{21}$$

where $\mathbf{H} := \mathbf{F}\mathbf{S}_0$, $\mathbf{S} := \mathbf{W}^{-1}$ and $\mathbf{S}_0 := \mathbf{S}_0^{-1}$. It should be noted that the matrices $\mathbf{A}_u$ and $\mathbf{B}_u$ contain the uncertain matrices $\mathbf{A}_d$ and $\mathbf{B}_d$; thus, (19) should hold for all $(\mathbf{A}_d, \mathbf{B}_d) \in\in \Psi$. To ensure that (19) is met for all $(\mathbf{A}_d, \mathbf{B}_d) \in\in \Psi$, we should verify that the condition is satisfied at all corners of the set $\mathbf{\Psi}$ i.e.,

$$\begin{bmatrix} \mathbf{S}_0 & \mathbf{S}^T \mathbf{A}_{ui}^T + \mathbf{H}^T \mathbf{B}_{ui}^T \\ \mathbf{A}_{ui}\mathbf{S}_0 + \mathbf{B}_{ui}\mathbf{H} & \mathbf{S} \end{bmatrix} > 0, \ (i = 1, 2, 3, 4), \tag{22}$$

where $\mathbf{A}_{ui} := \begin{bmatrix} \mathbf{A}_i & 0_{2\times 2} \\ -\mathbf{C} & \mathbf{I}_{2\times 2} \end{bmatrix}$, $\mathbf{B}_{ui} := \begin{bmatrix} \mathbf{B}_i \\ 0_{2\times 2} \end{bmatrix}$, $(i = 1,\ 2,\ 3,\ 4)$.

Summarizing the above discussion, a closed-loop system (16) is asymptotically stable if there exist symmetric positive definite matrices $\mathbf{S}$, $\mathbf{S}_0$ and a matrix $\mathbf{H}$ such that (20) holds, and the stabilizing gain is given as follows:

$$\mathbf{F} = \mathbf{H}\mathbf{S}_0^{-1}. \tag{23}$$

Suppose that $\mathbf{W}_0 < \alpha \mathbf{W}$ or

$$\mathbf{S} < \alpha \mathbf{S}_0\ (0 < \alpha < 1). \tag{24}$$

Then, (18) implies that for $k > 0$,

$$\begin{aligned} &\overline{x}^T(k)(\mathbf{A}_a + \mathbf{B}_a \mathbf{F})^T \mathbf{W} (\mathbf{A}_a + \mathbf{B}_a \mathbf{F})\overline{x}(k), \\ &= \overline{x}^T(k+1)\mathbf{W}\overline{x}(k+1) < \overline{x}^T(k)\mathbf{W}_0\overline{x}(k) < \alpha\overline{x}^T(k)\mathbf{W}\overline{x}(k). \end{aligned} \tag{25}$$

It can be expected that a small α would give a fast convergence of $\mathbf{z}$ to the origin. Therefore, to obtain optimal gain $\mathbf{F}$ such that the convergence time is minimized, the following optimization problem should be solved.

$$\underset{\substack{\mathbf{S},\mathbf{S}_0>0, \\ \alpha>0,\mathbf{H}}}{\text{Minimize}} \quad \alpha \,\text{subject to}\,(20)\text{and}\,(22) \quad . \tag{26}$$

This optimization scheme is a generalized eigenvalue problem that can be solved efficiently by MATLAB Toolbox. The convergence of this control method can be found in [20].

It can be noted that the controller with optimal gain $\mathbf{F}$ determined by solving problem (23) satisfies the condition (17) and guarantees the overall closed-loop stability for any of the variations on the filter's inductance L and resistance R as long as it stays within the uncertain range (9).

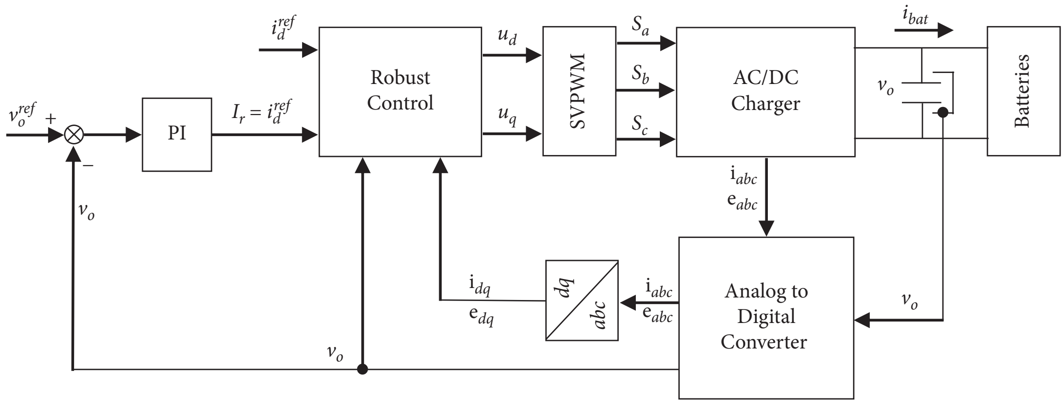


Figure 2: Block diagram of CV mode control.

5. Outer-Loop Charging Control

To perform the battery charging process, most of the battery manufacturers recommend two charging stages: constant current (CC) followed by constant voltage (CV). The battery is charged with a constant current until the voltage reaches the recommended maximum voltage, then the voltage is maintained constant until the current consumed by the battery falls to a residual value. The control of these two charging states is discussed in this section.

5.1. Constant Voltage (CV) Charging Mode. Here, the outer-loop PI control for constant voltage charging is discussed. Suppose that the dynamics of the inner-loop control in the previous section are considerably fast so that we could assume.

$$i_{\text{con.}}(t) \approx I_r(t), \tag{27}$$

for some current reference $I_r(t)$. Let I_r be the output of the outer-loop control, i.e.,

$$I_r(t) = K_p\left(v_o^{\text{ref}} - v_o(t)\right) + K_i \int v_o^{\text{ref}} - v_o(t)\text{d}t, \tag{28}$$

where v_o^{ref} is the constant voltage reference and $v_o(t)$ is the output voltage. From (5) and (25), we get

$$C\frac{dv_o(t)}{dt} + K_p\left(v_o^{\text{ref}} - v_o(t)\right) + K_i \int (v_o^{\text{ref}} - v_o(t))dt - i_{\text{bat.}}(t). \tag{29}$$

or

$$C\frac{d^2 v_o(t)}{dt} = K_p\frac{dv_o(t)}{dt} + K_i v_o(t) = K_i v_o^{\text{ref}}. \tag{30}$$

The K_i and K_p gain can be determined by considering the characteristic polynomial of (27) and can be given as follows:

$$\Delta(s) = s^2 + 2\zeta\omega_r s + \omega_r^2. \tag{31}$$

for some appropriate value of ζ and ω_r^2; we get

$$\begin{aligned} K_i &= \omega_r^2, \\ K_p &= 2\zeta\omega_r. \end{aligned} \tag{32}$$

The control diagram of the constant voltage control of the three-phase bidirectional charger is shown in Figure 2. The battery voltage is fed-back to the out-loop controller, which produces a reference current $i_r = i_q^{ref}$. A conventional phase-locked loop (PLL) is used in the controller to obtain the phase-angle of the grid voltage.

5.2. Constant Current (CC) Charging Mode. In the constant current charging stage, the battery pack is charged with a fixed current until the voltage reaches the recommended maximum voltage, then switch to the constant voltage charging stage. For the control of this constant current charging mode, an outer-loop PI is utilized to generate a reference signal $i_r = i_q^{\text{ref}}$ for inner-loop robust control with the same concept as CV charging discussed in the previous section. The control structure of the proposed CC charging control is validated as shown in Figure 3.

The control structure of both CC and CV charging modes are almost identical, however, the main difference is the use of outer-loop feedback; i_{bat} and v_o for CC and CV charging modes, respectively.

6. Discharging Control

Unlike CC and CV, this control scheme does not require the outer-loop controller; however, an uncomplicated computation of the reference state $\mathbf{x}_{ref}$ is needed. The discharging controller allows the battery charger delivers constant power back to the grid with a given reference P_{ref}.

Now, let us consider how to compute the reference state $\mathbf{x}_{ref}$ for the proposed robust controller. The instantaneous active and reactive power can be represented in the $\alpha\beta$-frame [21] as follows:

$$\begin{bmatrix} P_o \\ Q_o \end{bmatrix} = \frac{3}{2}\begin{bmatrix} e_\alpha & e_\beta \\ e_\beta & -e_\alpha \end{bmatrix}\begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix}, \tag{33}$$

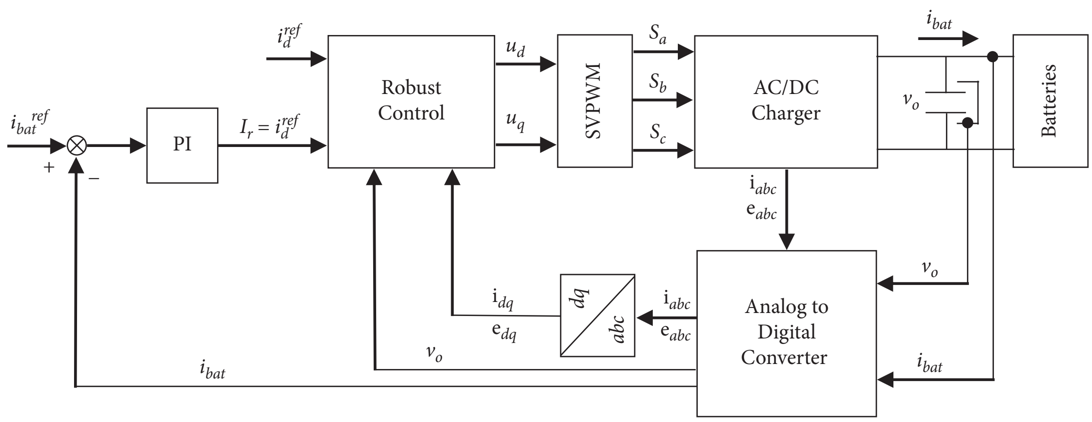


Figure 3: Block diagram of CC mode control.

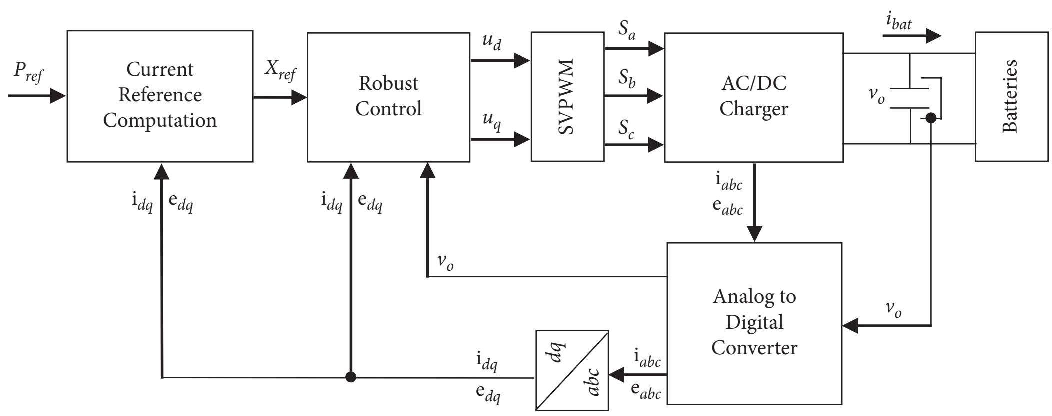


Figure 4: Block diagram of discharging mode control.

where $i_{\alpha\beta}$, $e_{\alpha\beta}$, P_o, and Q_o are grid-current in $\alpha\beta$-frame, grid-voltage in $\alpha\beta$-frame, grid active power and grid reactive power, respectively. Then, the relation (31) can be transformed to dq-frame as follows:

$$\begin{bmatrix} P_o \\ Q_o \end{bmatrix} = \frac{3}{2} \begin{bmatrix} e_d & e_q \\ -e_q & e_d \end{bmatrix} \begin{bmatrix} i_d \\ i_q \end{bmatrix}. \quad (34)$$

i_{dq} and e_{dq} are grid-current and voltage in dq-frame, respectively. From (32), the grid-current can be computed as follows:

$$\begin{bmatrix} i_d \\ i_q \end{bmatrix} = \frac{2}{3} \begin{bmatrix} e_d & e_q \\ -e_q & e_d \end{bmatrix}^{-1} \begin{bmatrix} P_o \\ Q_o \end{bmatrix}. \quad (35)$$

or

$$\begin{bmatrix} i_d^{ref} \\ i_q^{ref} \end{bmatrix} = \frac{2}{3} \begin{bmatrix} e_d & e_q \\ -e_q & e_d \end{bmatrix}^{-1} \begin{bmatrix} P_{ref} \\ Q_{ref} \end{bmatrix}. \quad (36)$$

In order to maintain a unity power factor, reactive power should be eliminated, and the reference can be computed as follows:

Table 1: Simulation parameters.

Parameters	Value
Grid phase-voltage	60 V
DC-link capacitor	4700 μF
Filter resistance	0.1 Ω
Filter inductance	5 mH
Sampling rate	10 kHz
Constant current reference	5 A
Constant voltage reference	107 V

$$\mathbf{x}_{ref} := \begin{bmatrix} i_d^{ref} \\ i_q^{ref} \end{bmatrix} = \frac{2P_{ref}}{3M} \begin{bmatrix} e_d \\ e_q \end{bmatrix}, \quad (37)$$

where $M = e_d^2 + e_q^2$. The reference state $\mathbf{x}_{ref}$ allows the charger to deliver constant power back to the grid with a given reference P_{ref}.

It can be noted that a negative power reference P_{ref} results in reverse current flowing, in another word current flow from batteries to the grid. We can charge the batteries with constant power by the positive P_{ref}. Moreover, the active and reactive power can be regulated directly by adjusting P_{ref} and Q_{ref} in (34), then the reference state can be obtained. The control structure of the proposed discharging control is validated as shown in Figure 4.

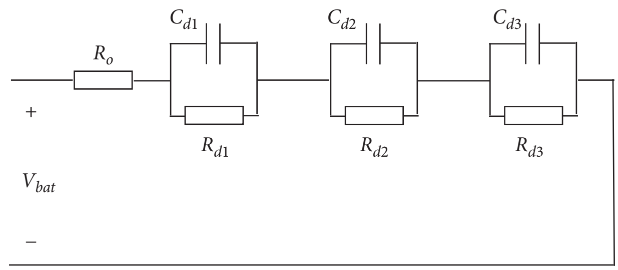


Figure 5: Battery equivalent circuit.

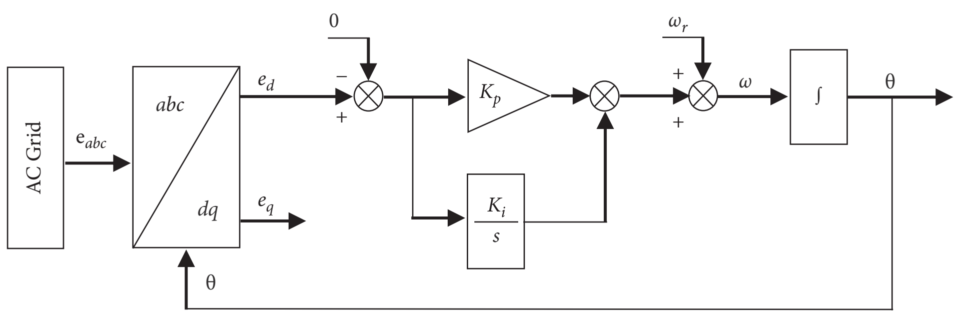


Figure 6: Structure of conventional phase-locked loop.

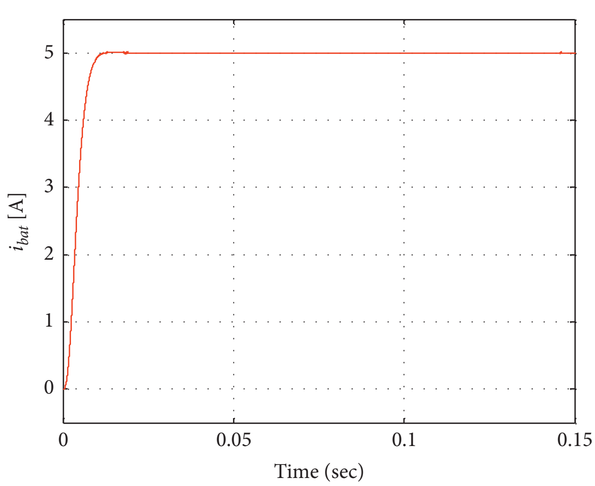


Figure 7: Transient response of output current in CC mode.

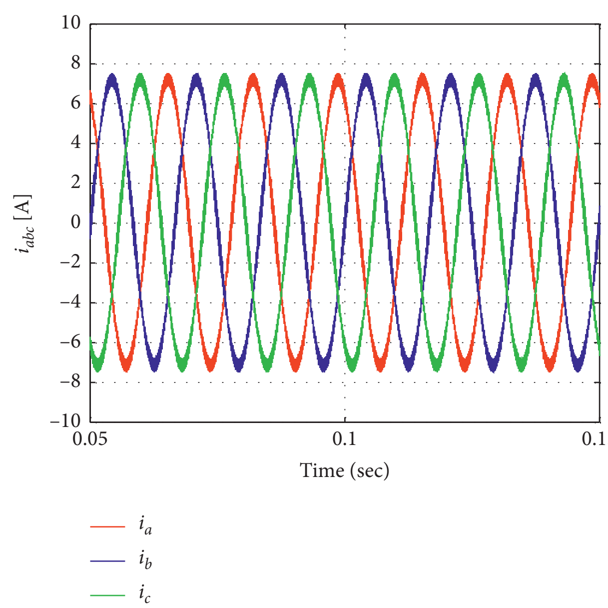


Figure 8: Steady-state grid current in CC mode.

7. Simulation Results

This section presents the results of the simulation on a three-phase AC/DC bidirectional charger to verify the efficacy of the proposed method. The simulation is implemented using the PSIM simulation tool and MATLAB LMI toolbox to obtain robust gain for the inner-loop controller. The parameters of the system are shown in Table 1. The control algorithm is conducted using a DLL block from Microsoft Visual Studio and the sampling rate is set to 10 kHz. An equivalent circuit in Figure 5 is used for the simulation studies.

The implementation of the proposed control strategy can be summarized as follows:

Step 1: Derive the discrete-time model based on (8) using the nominal value of inductance L and resistance R.

Step 2: Choose an initial uncertainty range of the parameters (11), e.g., $\mu = 1.1$, and corresponding set $\mathbf{\Psi}$.

Step 3: Compute the state feedback gain $\mathbf{K}$ and integrator gain $\mathbf{L}$ by solving the optimization problem (23).

Step 4: Implement the control (12) to the charger.

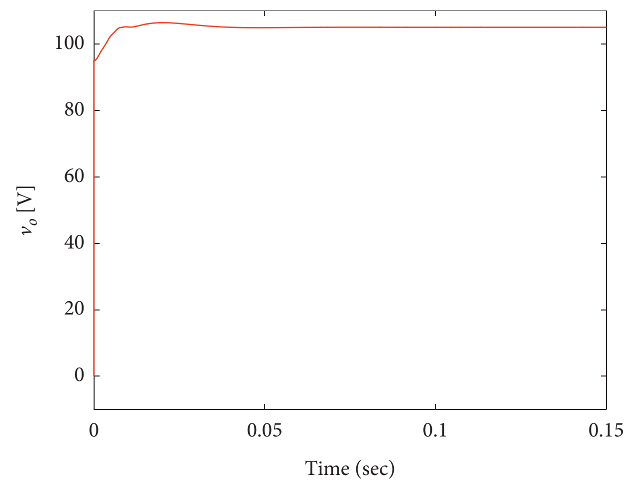
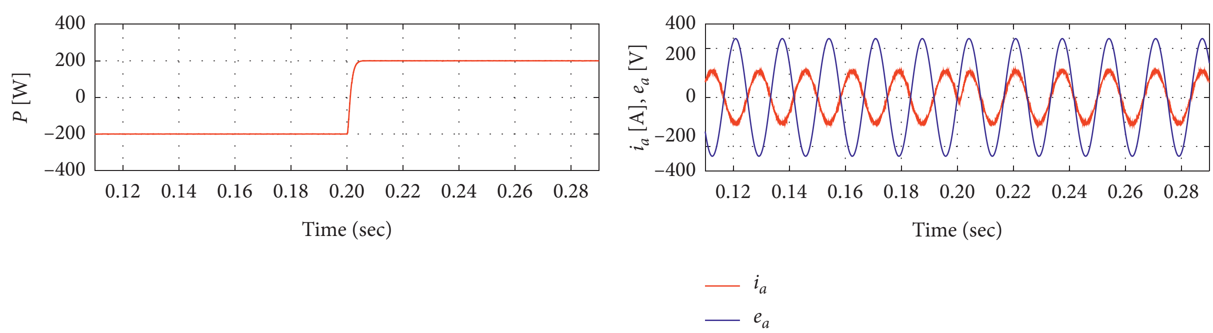


Figure 9: Transient response of output voltage in CV mode.



(a) (b)

Figure 10: (a) Active power and (b) grid voltage and current during discharging and charging mode.

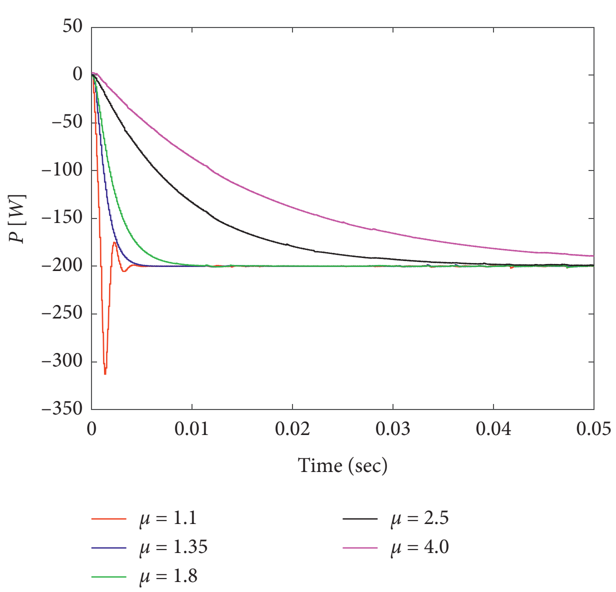


Figure 11: Active power using different uncertainties range μ in discharging mode.

Figure 12: Lithium iron phosphate (LiFePO4) battery pack.

Step 5: If the closed-loop system shows serious overshoot or becomes unstable, then adjust the uncertainty range, i.e., raise the value of μ and repeat the procedure from Step 3.

Step 6: After the closed-loop system becomes stable, then apply the outer-loop control for CC or CV.

In this paper, a synchronous reference frame phase-locked loop (PLL) is used to estimate the frequency and phase angle of the grid voltage [22]. The control structure of the conventional PLL is shown in Figure 6.

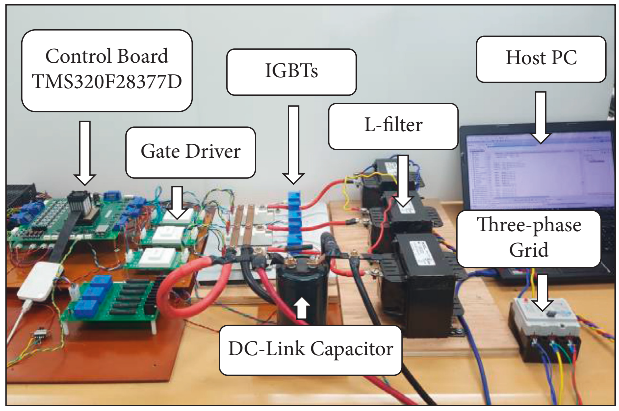


FIGURE 13: Experimental setups.

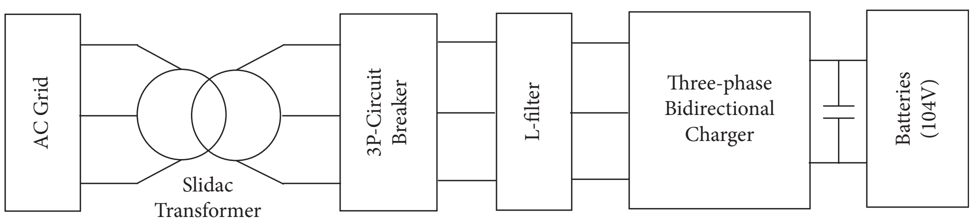


FIGURE 14: A simplified experimental setup circuit.

TABLE 2: Parameters of the prototype.

Parameters	Value
Grid phase-voltage	60 V (max)
DC-link capacitor	4700 μF
Filter resistance	0.2 Ω
Filter inductance	5 mH
Sampling rate	10 kHz
Constant current reference	5 A
Constant voltage reference	107 V
Battery ($LiFePO_4$)	102.4 V (20 Ah)

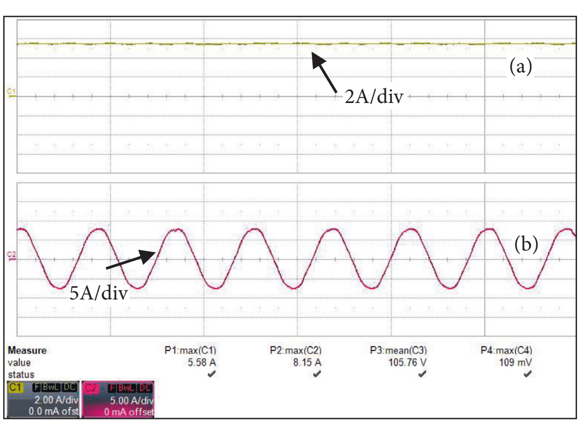


FIGURE 15: Experimental results of (a) battery current and (b) phase-A grid current in CC mode.

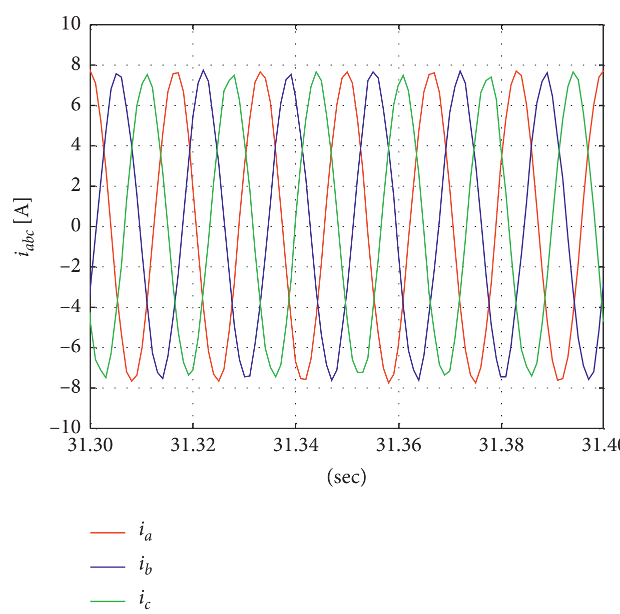
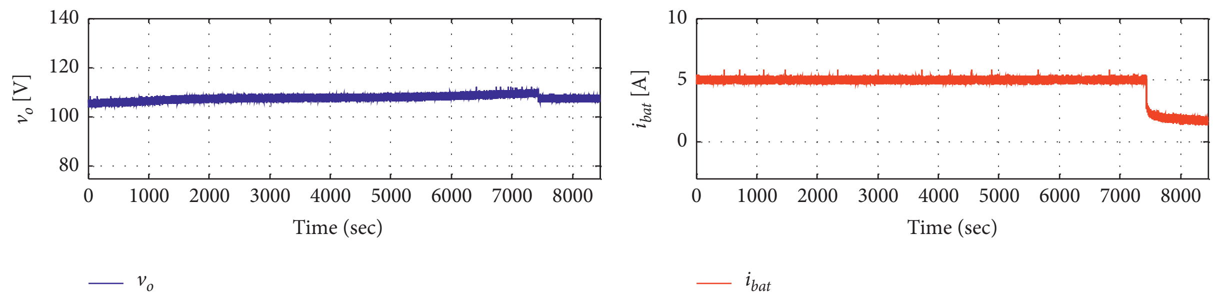


FIGURE 16: Experimental results of three-phase grid-current in CC mode.

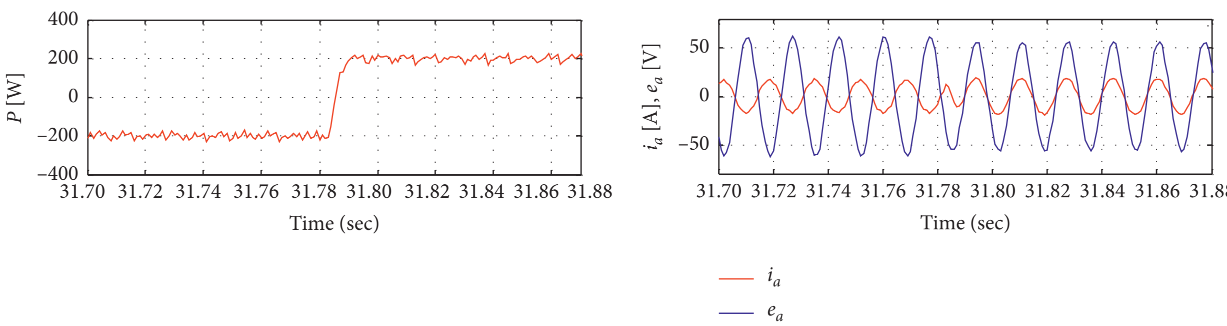
Here, the simulation performances of the proposed bidirectional charger are discussed. The transient response of the output current to the battery in CC mode is shown in Figure 7. This is the first charging stage of the batteries followed by constant voltage (CV) charging mode. We can see that the proposed robust control provides a fast-transient performance and smooth output current. The steady-state performance of the three-phase grid current is validated in Figure 8.

Figure 9 shows the transient performance of the output voltage in constant voltage CV charging mode. The bidirectional charger switches to this stage when the battery's voltage reaches a certain point after constant current CC charging mode. The outer-loop voltage control generates the



(a) and (b)

Figure 17: Experimental results of (a) battery voltage and (b) battery current in CC/CV.



(a) (b)

Figure 18: Experimental results of (a) active power and (b) grid-voltage and current during discharging and charging mode.

reference to inner-loop control (12) as shown in Figure 2. It can be seen that the output voltage to batteries is considerably fine.

For the simulation study in Figure 10(a), the discharging and charging of batteries with constant active power is validated. The battery is discharged with 200 W power at $t = 0.11$ s then switch to charging at $t = 0.29$ s with 200 W. It can be seen that the settling time to steady-state for both points is considerably fast and with smooth output power. Figure 10(b) shows phase-A grid voltage and current. We can see that the voltage and current are in 180° phase difference in discharging stage and change to in-phase during the charging period. It can be noted that all the aforementioned simulation results were carried out using the same uncertainty range ($\mu = 1.35$) because within this range we can obtain fast performance and no overshoot.

From Figure 11, a further study of using different uncertainty ranges is shown. The different selection of μ = (1.1, 1.35, 1.8, 2.5, and 4.0) in the equations (11a) and (11b) was made. From the figure, we can conclude that the use of $\mu = 1.1$ results in overshoot performance while sluggish performances are obtained with $\mu = 2.5$ and 4.0. Thus, a choice of μ between 1.35 and 1.8 would be considerable.

8. Experimental Results

For the experiment, a three-phase AC/DC converter with L-filter is used to charge 102.4 V Lithium iron phosphate ($LiFePO_4$) batteries. The proposed robust control was implemented on the TMS320F28377D digital signal processor with a sampling rate of 10 kHz. The battery packs consist of 64 cells, and the 32 pairs are connected in series. The actual battery pack is shown in Figure 12. A slide transformer is used to drop the grid voltage to a proper level to charge 102.4 V battery packs and the experimental setup is shown in Figure 13. A simplified experimental setup circuit is provided in Figure 14. The parameters of the experimental prototype are shown in Table 2.

Figure 15 shows experimental performances of battery charging current (a) and the phase-A grid-current (b) in steady stead with the reference current 5 A. It can be seen that the bidirectional charger can provide a smooth constant charging current to the batteries. Note that all the experimental data below is obtained by CAN communication from the control board.

In Figure 16, the steady state three-phase grid-current in charging mode is validated. We can see that a considerable balanced sinusoidal grid-current is obtained using this proposed control.

Figure 17 shows a full process of charging using CC and followed by CV. The battery is charged with constant 5 A until $t = 7400$ s then switched to constant voltage mode. From the figure, we can observe that the battery voltage is increasing to maintain a constant current. However, during the constant voltage charging stage, the battery current is dropping as time goes on.

For the experimental results in Figure 18(a), the discharging and charging of batteries with constant active power is shown. The battery is discharged with constant power, 200 W, then switch to the charging stage with 200 W. We can see that the settling time to steady-state for both points is considerably fast. Figure 18(b) shows a three-phase grid-current in discharging mode followed by charging mode. In both discharge and charging cases, an almost unity power can be obtained.

9. Conclusions

This paper describes a robust control strategy for a three-phase off-board bidirectional charger for an electric vehicle without using a DC-DC converter as an interface between a three-phase AC-DC converter and batteries. The conventional constant current (CC) and constant voltage (CV) charging mode are considered to provide a fast-charging performance for the batteries. The bidirectional charger also allows using of the electric vehicle as an energy storage system for the power grid. The proposed control consists of inner-loop robust control and outer-loop conventional PI control. For the inner-loop robust control, a state feedback controller with integral action is employed in dq-synchronous frame. The set of stabilizing gains of this controller are determined by an LMI-based optimization so that the convergence time to steady stead is minimized in the occurrence of the parametric uncertainties of the L-filter. It can be noted that the uncertainty range of the inductance and resistance can be considered a design parameter. Thus, its choice should be made depending on the resulting performances. From the simulation and experimental results, we can see that the proposed control for the bidirectional charger has considerable performance in both charging and discharging modes. The shortcoming of this proposed charger is that it is not capable of charging low voltage batteries due to the lack of a DC-DC converter as an interlink between the batteries and an AC-DC converter. The additional implementation of disturbance and state observers will be included in the future work of this research.

Abbreviations

CAN: Controller area network
CC: Constant current
CV: Constant voltage
EV: Electric vehicle
G2V: Grid to vehicle
LMI: Linear matrix inequality
PHEV: Plug-in hybrid electric vehicle
PI: Proportional integral
PLL: Phase-locked loop
PR: Proportional resonant
V2G: Vehicle-to-grid
V2H: Vehicle-to-home
L: Inductive filter
R: Filter resistance
C: Capacitive filter
$v_o(t)$: Output voltage
S_{abc}: Switching vector in abc-frame
$\mathbf{i}_{abc}(t)$: Grid current vector in abc-frame
$\mathbf{i}_{\alpha\beta}(t)$: Grid current vector in $\alpha\beta$-frame
$\mathbf{i}_{dq}(t)$: Grid current vector in dq-frame
$\mathbf{u}(t)$: Continuous time control input
E_m: Grid voltage magnitude
ω: Angular frequency
$i_{con.}$: Converter current
$i_{bat.}$: Battery current
$\mathbf{x}(k)$: Discrete-time state
$\mathbf{u}(k)$: Discrete-time control input
$L_{\min}$: Lower bounce filter inductance
$L_{\max}$: Upper bounce filter inductance
$R_{\min}$: Lower bounce filter resistance
$R_{\max}$: Upper bounce filter resistance
$\mathbf{\Psi}$: Uncertainty set
μ: Uncertainty range
$\mathbf{w}(k)$: Integral state
$\mathbf{L}$: Integral gain
$\mathbf{K}$: State feedback gain
$\mathbf{x}_{ref}$: Reference state
$\mathbf{W}$: Weighting matrix
$\overline{x}(k)$: Augmented state
K_i: Outer loop integral gain
K_p: Outer loop proportional gain
P_o: Output active power
Q_o: Output reactive power
$\mathbf{e}_{\alpha\beta}$: Grid voltage vector in $\alpha\beta$-frame
$\mathbf{e}_{dq}(t)$: Grid voltage vector in dq-frame
P_{ref}: Active power reference
Q_{ref}: Reactive power reference.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Research Article

An Effective Charger for Plug-In Hybrid Electric Vehicles (PHEV) with an Enhanced PFC Rectifier and ZVS-ZCS DC/DC High-Frequency Converter

G. Kanimozhi,[1] **L. Natrayan**,[2] **S. Angalaeswari**,[3] **and Prabhu Paramasivam**[4]

[1]*Centre for Smart Grid Technologies, School of Electrical Engineering, Vellore Institute of Technology, Chennai, Tamil Nadu, India*
[2]*Department of Mechanical Engineering, Saveetha School of Engineering, SIMATS, Chennai 602105, Tamil Nadu, India*
[3]*School of Electrical Engineering, Vellore Institute of Technology, Chennai, Tamil Nadu, India*
[4]*Department of Mechanical Engineering, College of Engineering and Technology, Mettu University, Metu 318, Ethiopia*

Correspondence should be addressed to G. Kanimozhi; kanimozhi.g@vit.ac.in, L. Natrayan; natrayan07@gmail.com, and Prabhu Paramasivam; prabhuparamasivam21@gmail.com

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A plug-in hybrid electric vehicles (PHEV) charger adapter consists of an AC/DC power factor correction (PFC) circuit accompanied by a full-bridge isolated DC/DC converter. This paper introduces an efficient two-stage charger topology with an improved PFC rectifier as front-end and a high-frequency zero voltage switching (ZVS). Current switching (ZCS) DC/DC converter is the second part. The front-end converter is chosen as bridgeless interleaved (BLIL) boost converter, as it provides the advantages like lessened input current ripple, capacitor voltage ripple, and electromagnetic interference. Resettable integrator (RI) control technique is employed for PFC and DC voltage regulation. The controller achieves nonlinear switching converter control and makes it more resilient with the faster transient response and input noise rejection. The second stage incorporates a resonant circuit, which helps in achieving ZVS/ZCS for inverter switches and rectifier diodes. PI controller with phase shift modulator is used for second-stage converter. It improves the overall efficacy of the charger by lowering the switching losses, lowering the voltage stress on the power semiconductor devices, and reversing recovery losses of the diodes. The simulations and experimental results infer that the overall charging efficiency increases to 96.5%, which is 3% higher than the conventional two-stage approach using the interleaved converter.

1. Introduction

In order to reduce the fuel consumption and fuel emission, the world is moving towards eco-friendly vehicles, [1] namely electric vehicles (EV), hybrid electric vehicles (HEV), and PHEV. Highly efficient batteries, its fast-changing technologies, and charging infrastructure are the key sources for the electric vehicles. Battery chargers are crucial in the field of battery and electric car technology [2]. A traditional combustible engine plus an electric engine powered by a pluggable external electric source propels PHEVs [3]. In normal driving conditions, PHEVs can store enough electricity from the grid to drastically reduce their gasoline usage [4]. The recent developments in PHEV motor drive and battery charging technologies have increased the demand for PHEV vehicles in the market. Researchers focus on improving the same to speed up the commercialization of the vehicle in the market.

Batteries [5] such as nickel metal hybrid, lithium polymer, and lithium-ion are predominantly used in electric vehicles for its best efficiency, safety, energy density, and cost factor. At all power levels, a battery charger can allow unidirectional or bidirectional power transfer. The bidirectional power flow [6] includes a vehicle-to-grid (V2G) mode to the grid-to-vehicle interface (G2V). In a utility-connected microgrid, a battery charger configuration for PHEV applications using a back-to-back (B2B) converter is also proposed [7]. Depending on the vehicle's power requirements, this proposed structure can operate in four different modes: grid-to-vehicle (G2V), microgrid-to-vehicle (M2V), vehicle-to-grid (V2G), and vehicle-to-microgrid (V2M).

The IEC-62196 specifies the general parameters of the charging process [4], and therefore, how energy is delivered. In order to charge the automobiles, users have four options. They are slow charging, semi-fast charging, fast charging, and ultrafast charging. Two different types of chargers for charging the battery are considered, namely high-speed charger and on-board charger [8]. PHEV applications support on-board charger for residential charging. From a 230 V supply, 3.3 kW on-board charger can charge a 16 kWh exhausted battery pack in around 4 hours.

The charger architectures [8] are broadly classified as single-stage and two-stage chargers. Two-stage architecture is preferred, as it gives low-frequency ripple rejection. Front part of two-stage architecture is AC-DC converter, and back end has DC/DC converter. The power architecture of a two-stage battery charger depicted in Figure 1 includes AC/DC PFC circuit accompanied by a second part isolated DC/DC converter.

A variety of PFC rectifier circuits with linear and nonlinear control methods [9] have been developed as front-end converters. A multilevel converter configuration is the viable choice if larger power ratings are required. Most commonly used topologies for the front-end converter are dual boost converter [7], bridgeless PFC converter [10], interleaved PFC boost converter [11], and phase shifted boost converter [12]. The interleaving concept reduces the current ripple at the supply end and also EMI filter requirement. On the other hand, the drawbacks of the conventional interleaved converters include increased output voltage ripple, cost, design complexity, the thermal problem due to the presence of diode bridge rectifiers, voltage and current stress on the semiconductor devices, and electromagnetic interferences (EMI).

A BLIL PFC boost converter with four-channel interleaving is considered as front-end converter, since it overcomes the drawbacks of the conventional converters. The second part of the two-stage charger is an isolated resonant DC/DC converter. Various topologies for obtaining zero voltage switching are available. Higher circulating primary winding current is one of the major downsides of the traditional isolated DC/DC converter to attain ZVS resulting in greater conductive losses of switches. Alternatively, ZVS eliminates noise and harmonics in high-frequency converters. Many topologies with soft switching technique, such as phase shifted ZVS topology [13], LLC resonant topology [14], and RCD voltage clamping [15], are reported in the literature to diminish the switching losses, voltage stress across the switches, and diode's reverse recovery loss. The proposed second-stage resonant converter overcomes the above-mentioned losses with lesser number of components, thereby increasing the overall efficiency of the charger. Miralinaghi et al. [16] suggested scheme on operation and integration of two buck-boost converter based on a single-phase bidirectional inverter under a maximum power point trackers (MPPT) on DC distribution system. The power factor correction and grid connection fulfilment were

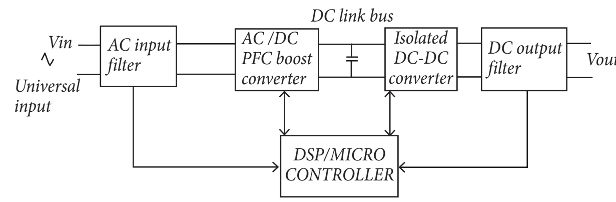


Figure 1: Block diagram of the battery charger unit.

obtained by bidirectional inverter with a full-bridge configuration. The power flow between DC bus and AC grid was controlled by an inverter control system, and it was regulated DC bus to a certain range of voltages [16].

Tran suggested scheme on operation and integration of two buck/boost converter based on a single-phase bi-directional inverter under a maximum power point trackers (MPPT) on DC distribution system. With a thin PV array, the MPPT technique was formed by two buck and boost converter, it reduced the voltage stress. The power factor correction and grid connection fulfilment were obtained by bidirectional inverter with a full-bridge configuration [17]. Miralinaghi et al. [18] suggested a scheme on soft switching charging and discharging converter with the zero-voltage discharge function. The battery voltage can be discharged by the converter until it becomes zero. In the charging operation at turn-on period, the zero voltage switching was achieved, and in discharging operation at turnoff period, the zero current switching was achieved [18]. He et al. [19] suggested scheme on single DC single source with less magnetite topologies for minimizing the power balance issues. For minimizing the zero-sequence current, a sine-triangle pulse width modulation was used. To obtain a staircase voltage waveform using power electronic switches under low-rated based on multilevel inverter concept. As that the requirement of series-connected switches increases, it depends on the number of increasing voltage level [19]. This paper introduces an efficient two-stage charger topology with improved PFC rectifier as front end with a nonlinear controller and a high-frequency ZVS-ZCS DC/DC converter as the second stage with ACM controller as displayed in Figure 2.

This article is structured in the following manner: Section 2 designates the first stage of battery charger system with nonlinear PFC algorithm and the second stage is resonant DC/DC converter explained in Section 3. The requisite designed equations of the converter and its specifications of the suggested battery charger are addressed in Section 4. The simulation results are detailed in Section 5. Finally, Section 6 carries the conclusion report based on the results obtained.

2. Front-End PFC Boost AC/DC Converter

BLIL PFC boost converter [20–23] shown in Figure 2 includes four inductors ($L1, L2, L3$, and $L4$), four power MOSFET's ($Q1$ to $Q4$), four diodes ($D1$ to $D4$), and an intermediate DC link capacitor (C_{01}). As the term suggests, the bridge rectifier with diodes is abolished. Compared with the traditional interleaved boost converter, four channel

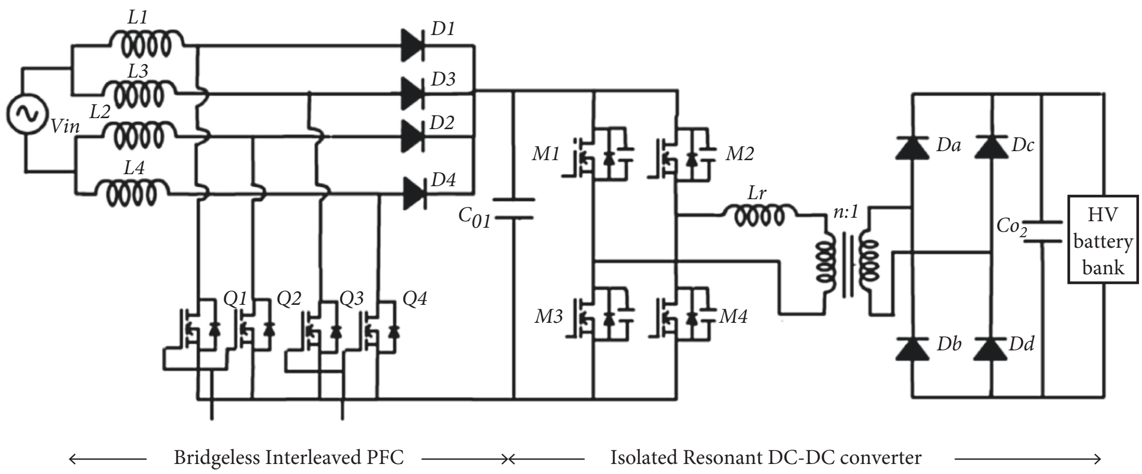


Figure 2: Proposed battery charger unit.

interleaving lessened the input current ripple. The total current flowing through the inductors $L1/L2$ and $L3/L4$ will be the input current. Since the ripple current in the inductors [$L1/L2$ and $L3/L4$] are now out of phase, they negate each other, thus minimizing the ripple of input current [24]. Interleaving decreases output capacitor current ripple, current stress on the devices, and, furthermore, the circuit EMI [25].

BLIL boost converter is implemented with the PFC control algorithm, which improves power factor and power quality of the input current according to IEC 61000-2-3 standard, and the load voltage is regulated to the preferred value. The PFC [26, 27] is designed in several ways, such as boundary conduction mode (BCM), continuous conduction mode (CCM), and discontinuous conduction mode (DCM). Average current mode (ACM) control is one of most commonly used methods in boost PFC converters to accomplish high power factor and minimal distortion. Any disturbance in the line voltage is compensated in the ACM control technique, increasing the output voltage's immunity to variations in the supply line. This method drawback includes detecting input current, input voltage, output voltage, and multiplier circuit all of which add to the circuit complexity. When a transient occurs, the outer voltage loop reaction is slow, and it takes many switching cycles to achieve stability. These disadvantages are rectified by incorporating nonlinear control technique.

The BLIL boost converter considered in this work operates in CCM mode, and the control scheme incorporated is resettable integrator control technique. Resettable integrator (RI) technique [28–30] shown in Figure 3 is a nonlinear technique proposed for converters operating at constant frequency. This does not require input voltage sensor, multipliers, and input current error compensator as like average current mode control. The vital advantage of this control method is that it the harmonics are removed as well as the transients are traced. The output signal is combined here until it approaches the reference signal. The converter switching frequency, f_0, is much higher than the frequency of the input signal $x(t)$ or the reference signal $V_r(t)$, and therefore, $x(t)$ and $V_r(t)$ can be taken as fixed value. Let $y(t)$ be the output variable.

$$y(t) = \frac{1}{T_S}\int_0^{T_{\mathrm{on}}} x(t)\mathrm{d}t = \frac{1}{T_S}x(t)\int_0^{T_{\mathrm{on}}}\mathrm{d}t = x(t)\delta(t), \qquad (1)$$

where $\delta(t)$ is the duty cycle and T_s is the total interval. The power device's duty cycle is controlled when the chopped waveform equals the input reference as stated in the following equation:

$$\begin{aligned}\int_0^{T_S} x(t)\mathrm{d}t = \int_0^{T_S} V_r(t)\mathrm{d}t\ y(t) = \frac{1}{T_S}\int_0^{T_S} x(t)\mathrm{d}t \\ = \frac{1}{T_S}\int_0^{T_S} V_{\mathrm{ref}}(t)\mathrm{d}t = V_r(t).\end{aligned} \qquad (2)$$

In different converter topologies, this control approach may be extended to leading edge and trailing edge modulation. The theoretical waveform of the control technique is depicted in Figure 4. The sensed output voltage V_{sen} is fed to an amplifier. The amplified error voltage $V_c(t)$ is tuned by PI controller that is integrated with a resettable integrator, and for each switching cycle, a variable magnitude ramp voltage $V_m(t)$ is generated. The inductor current I_{sen} is compared with the ramp voltage as shown in Figure 3. When the voltages are equal, the integrator resets. Therefore, the integrator resets for each switching time and the ramp voltage begins at "0" for consecutive switching period. Thus, in one switching period this discards the supply-fed disturbances and load disruptions.

3. Isolated Resonant DC/DC Converter

The PHEV charger second part consists of an isolated resonant DC/DC converter [31], which can be operated in CCM, BCM, and DCM mode. In this case, the converter is operated in DCM mode, with high switching (100 kHz) frequency to lessen the passive components size, the ratio of transformer turns, and the current stress on primary end switches. The primary winding of the transformer is coupled

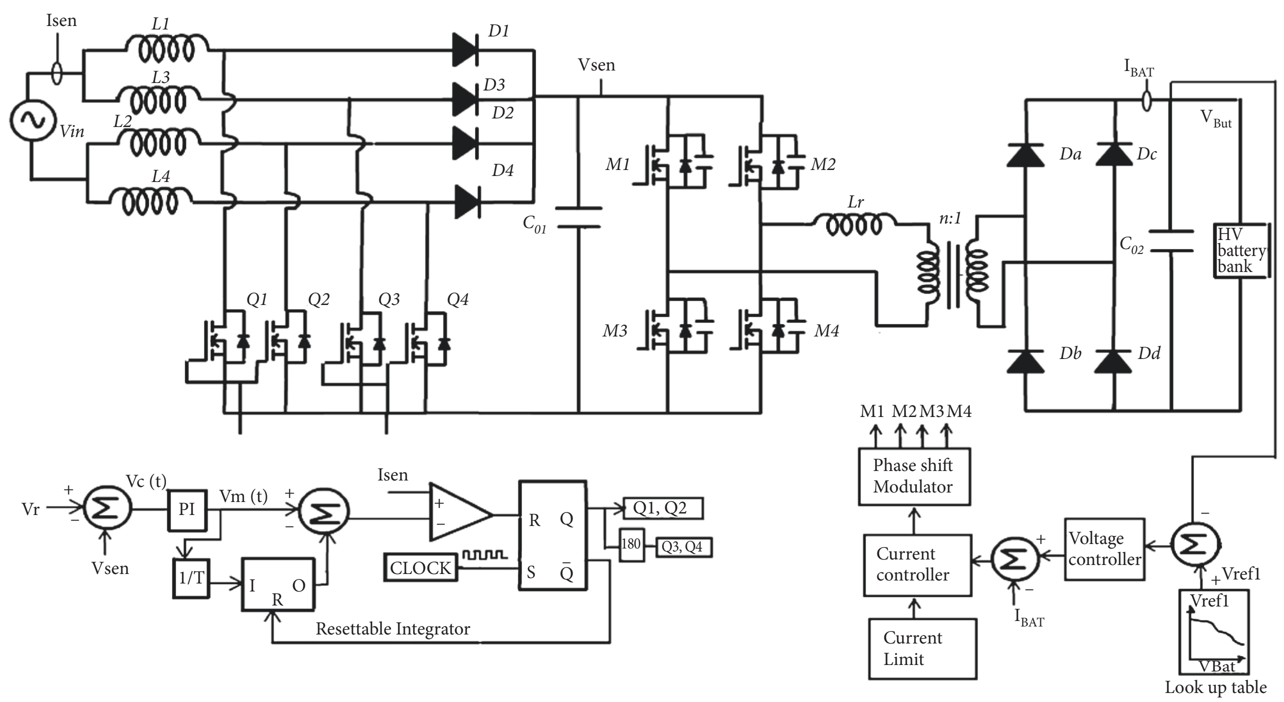


Figure 3: Overall control structure.

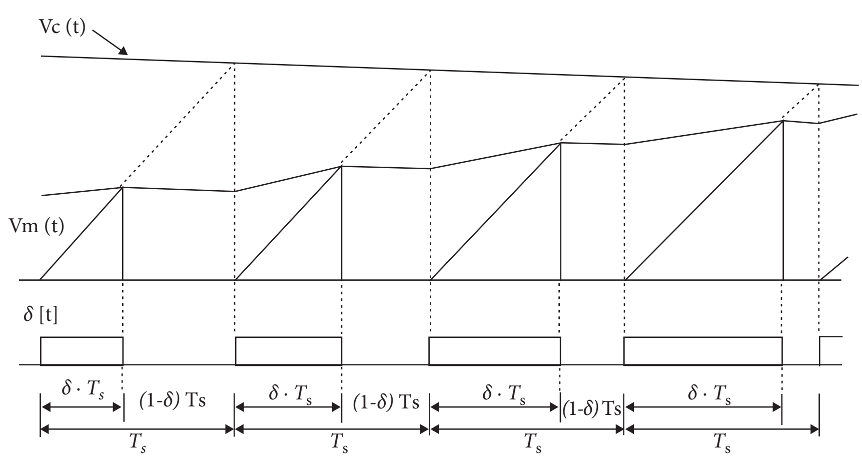


Figure 4: Theoretical waveform of RI technique.

to the inverter circuit as portrayed in Figure 2. The inverter switches and rectifier diode's resonant switching are achieved by fixing the duty cycle of the lower group devices of the inverter $M3$ and $M4$ as 50%, while upper switches ($M1$ and $M2$) are PWM controlled [32]. The power semiconductor devices are modelled with parasitic capacitances and parallel diodes. All the parasitic capacitances of switches and inductors are together taken in the output capacitance. Theoretical waveforms for the operation of isolated resonant DC-DC converter are shown in Figure 5.

It can be seen that the ZV switching-on and ZC switching-off is accomplished for the inverter's lower switches, while the upper leg devices attain ZCS turnoff. The diodes in the rectifier circuit connected next to the transformer secondary will accomplish zero current turnoff. At the time instant $t = to$, the power devices $M1$ and $M4$ are turned on and the current streams through $M1$-Lr- primary winding of the transformer and $M4$. At time $t = t_1$, $M1$ turns off and the primary current follows an alternative path via. M_4-parasitic capacitance of M_3 and Lr.

The resonant inductor's current i_{Lr} is expressed as follows:

$$i_{Lr}(t) = \frac{V\mathrm{dc} - (V_0/n)}{Lr}(T - t_0). \tag{3}$$

At the same interval, the diodes $Da\mathrm{D}_1$ and Dd will start D_4 conducting on the rectifier side. The direction of the secondary current through D_1-load and D_4 is achieved. Power devices $M1\mathrm{M}_1$ and M_4 have now attained ZCS during OFF state. At time instant $t = t_3$, the switches $M2M_2$ and $M3$ are

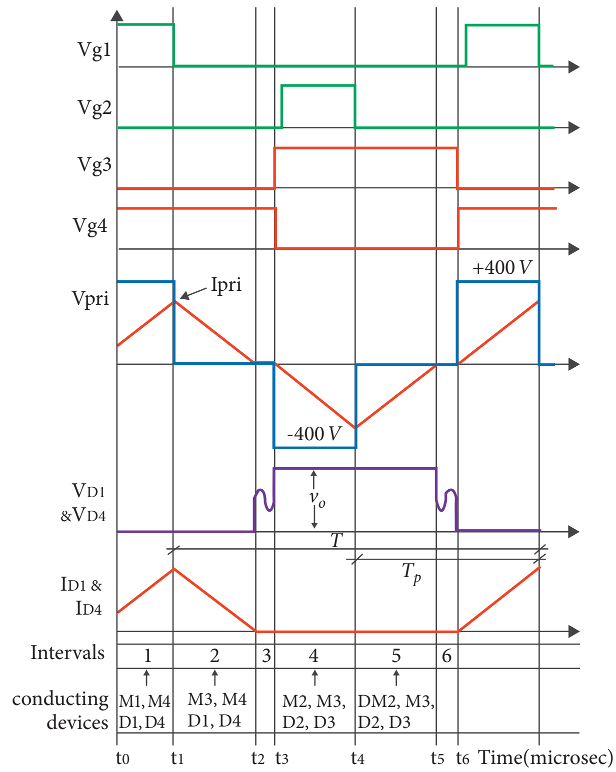


Figure 5: Theoretical waveform second-stage resonant isolated DC/DC converter.

triggered ON, and D_1 and D_4 are now reverse biased, while DbD_2 and D_3 are forward biased. The resonant inductor current is currently, as per the initial condition $i_{Lr}(0) = i_{\text{pri}} i_{L_r}(0) = i_E$, provided by the following equation:

$$i_{Lr}(t) = i_{\text{pri}} - \frac{V_o}{n * Lr}(T - t_1), \tag{4}$$

where i_{pri} is the primary current of the transformer. The time instants $t = t_4, t_5$, and t_6 are the negative equivalents of the intervals t_1 to t_3. For the diodes on the rectifier side of the circuit ZCS turn-on and ZCS turnoff are accomplished. The isolated resonant DC/DC converter removes the need of traditional RCD voltage clamping circuit in this case, thereby reducing the total losses and enhancing the charger performance.

The full-bridge DC/DC converter control method incorporates a phase shift of lagging leg switches with respect to leading leg switches realized by conventional ACM control as shown in Figure 3. Here, the battery terminal voltage of the battery is set to the current reference and the charging graph determines the power required to charge the battery bank. Thus, the full-bridge inverter duty ratio is determined by the charging curve and the terminal voltage of the battery.

4. Design Considerations

This section discusses the presented two-stage battery charger design. The four-channel interleaving inductors of BLIL boost rectifier are designed based on the input ripple current ΔI_L, and it is specified as

$$\Delta I_L = \frac{V_{\text{in}}\sqrt{2}D}{f s.Lb/2}, \tag{5}$$

where $V_{\text{in}} = \sqrt{2}Vs \sin \omega t$ is the maximum value of the input voltage, and f_s is the switching frequency of rectifier. $Lb = L1 = L2 = L3 = L4$ are boost inductors. Two inductors of equal value are connected to each phase. The duty cycle D is expressed as

$$D = 1 - \frac{V_{\text{inp}}}{V\text{bus}}, \tag{6}$$

where $V\text{bus}$ is the bus voltage of the boost converter. The output power P_o is given as

$$Po = V\text{bus} * I\text{bus}. \tag{7}$$

Here, Ibus is the rectifier output current. The MOSFET used in the rectifier has duty cycle $\delta_{Q(\theta)}$, and it is expressed as

$$\begin{aligned}\delta_Q(\theta) &= 1 - \frac{|V_{\text{in}}(\theta)|}{V_o}\\ &= 1 - \frac{V_p|\sin\theta|}{V_o},\end{aligned} \tag{8}$$

where V_p is the input peak value. Assuming the current flowing through the inductor as sinusoidal, its expression is given as follows:

$$i_{L=I_p|\sin\theta|}, \tag{9}$$

where I_P is the input current's maximum value. The instantaneous current of MOSFET $i_Q(\theta)$ and its root mean square (RMS) value $i_Q(\text{rms})$ may be given as follows:

$$i_{Q(\theta)=Ip|\sin\theta|}\delta_{Q(\text{rms})},$$

$$i_Q(\text{rms}) = \left[\frac{1}{\pi}\int_0^{\pi}\left[I_p|\sin\theta|\left(1 - \frac{V_p|\sin\theta|}{V_o}\right)\right]^2\right]^{1/2} d\theta. \tag{10}$$

The duty cycle of the diode $\delta_D(\theta)$ can be stated as

$$\delta_D(\theta) = 1 - \delta_Q(\theta) = \frac{V_{p|\sin\theta|}}{V_o}. \tag{11}$$

The instantaneous value of diode current is

$$i_D(\theta) = I_p|\sin\theta|\left(\frac{V_p|\sin\theta|}{V_o}\right). \tag{12}$$

RMS value of diode current can be expressed as

$$i_D(\text{rms}) = \left[\frac{1}{\pi}\int_0^{\pi}\left[I_p|\sin\theta|\left(\frac{V_p|\sin\theta|}{V_o}\right)\right]^2\right]^{1/2} d\theta. \tag{13}$$

The output capacitor current has low ($I_{c\text{-rms(low)}}$) and high-frequency components ($I_{c\text{-rms(high)}}$) and is given as

$$I_{c\text{-rms}}(\text{low}) = \frac{I_o}{\sqrt{2}} = \frac{\sqrt{2}}{2}\frac{P_o}{V_o},$$
$$I_{c\text{-rms}}(\text{high}) = \frac{Pin}{V_o}\sqrt{\frac{16V_o}{6\pi V_p} - \frac{P_o^2}{P_{in}^2}}. \quad (14)$$

The capacitor C_{01} is expressed as

$$C_{01} = \frac{2Po * T_h}{V^2\text{bus} - (V\text{bus} * 0.75)}, \quad (15)$$

where P_0 is the output power and T_h is the maximum hold up time for the line frequency 50 Hz.

$$G = \frac{V_o}{V\text{in}} = \frac{1}{1-D}. \quad (16)$$

And thus, the voltage stress V_{st} across the power devices is given as

$$V_{st} = GV\text{in} = V_o. \quad (17)$$

The second-stage isolated DC/DC converter with voltage gain (G) is formulated as follows:

$$G = \frac{V_o}{V\text{dc}} = \frac{2 * n}{1 + \sqrt{1 + 4 * k/D^2}}, \quad (18)$$

where k is the standardized time constant $(k = 4n^2 L_R/R_0 T)$ and n is the turn's ratio of the transformer, and it is given as

$$n = \frac{V_o}{V\text{dc} * D}. \quad (19)$$

The duty ratio for the inverter switch is set at 0.377 as it gives the optimal gain value. The turn's ratio of the transformer is obtained as 1.326 from (19). The voltage gain ranges from 0.1 to 0.5 for different values of D, and k from 0.1 to 1 has been calculated and plotted using MATLAB as shown in Figure 6. The resonant inductor value $(L_r L_r)$ is given as

$$L_r = \frac{k * R * T}{4 * n^2}$$
$$L_r = \frac{k * R_0 * T}{4 * n^2}, \quad (20)$$

where R is the output resistance of the converter and T is the switching interval. Thus, the value of L_r is 176 μH from (20). The RMS value of current passing through the inverter switches $M1$ and $M2$, $I_{M12(\text{rms})}$, is given as

$$I_{M12(\text{rms})} = \sqrt{\frac{1}{T}\int_{t_0}^{t_1} i_{Lr}(t)^2 \text{d}t}, \quad (21)$$

and the RMS value of current through inverter switches $M1$ and $M2$, $I_{M12(\text{rms})}$, is given as

$$I_{M12(\text{rms})} = \sqrt{\frac{1}{T}\left[\int_{t_0}^{t_1} i_{Lr}(t)^2 \text{d}t + \int_{t_1}^{t_2} i_{Lr}(t)^2 \text{d}t\right]}. \quad (22)$$

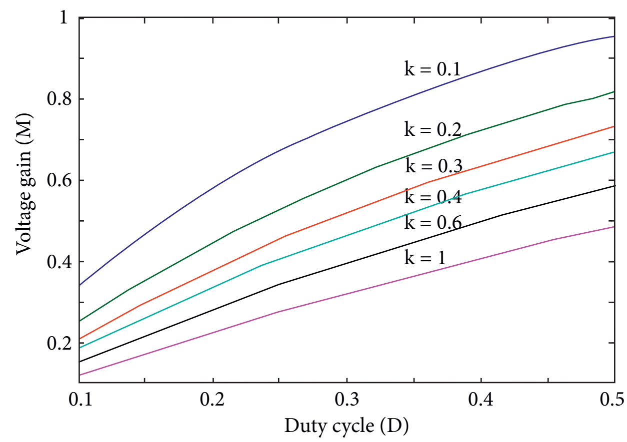


Figure 6: Voltage gain (M) versus duty cycle (D) plot for different values of k.

Table 1: Specifications of the proposed charger.

Parameters	Value (units)
Bridgeless PFC boost rectifier	
Power output (P_0)	300 W
Switching frequency (fs)	80 kHz
Inductors $(L1, L2, L3, L4)$	0.58 mH
Capacitor (C_1)	470 μF
Efficacy (η)	97%
Isolated resonant DC/DC converter	
Switching frequency (f_{sw})	100 kHz
Transformer turns ratio	1.326 : 1
Resonant inductor (L_r)	176 μH
Output capacitor (C_2)	470 μF
Efficacy (η)	96.5%

The average current through the antiparallel diodes of MOSFETs $M3$ and $M4$, I_{D34}, is given by

$$I_{D34} = \frac{1}{T}\int_{t_1}^{t_3} i_{Lr}(t)\text{d}t. \quad (23)$$

The output filter capacitor C_{02} value is determined using capacitor RMS current Ic_{02}.

$$Ic_{02} = \sqrt{\frac{1}{T_P}\int_{t_0}^{T_P} (i_r(t) - I_o)^2 \text{d}t},$$
$$C_{02} = \frac{I_{C02(\text{rms})}}{4\pi f_s V_r}. \quad (24)$$

The critical component value for the prototype is given in Table 1.

5. Simulation Results

The simulation of the proposed charger is carried out for 300 W using PSIM. The converter is simulated under varying supply conditions. Figure 7(a) shows the simulated dynamic response of the converter when the input voltage is adjusted from 230 V to 110 V at time $t = 0.48$ s using conventional control technique. After two cycles of lowering the supply

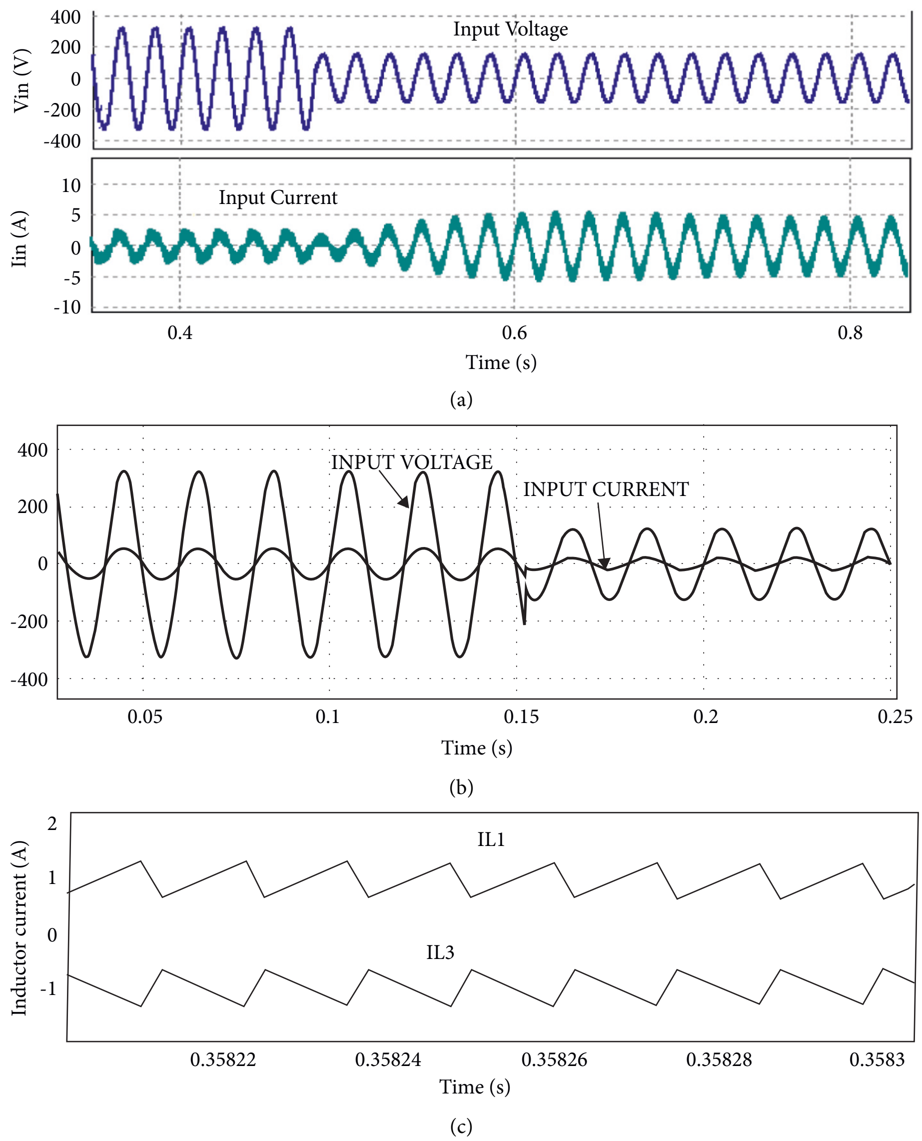


Figure 7: (a) Input supply voltage and current waveforms presenting power factor with 230 Vrm$_s$ and 110 Vrms for conventional controller. (b) Input supply voltage and current waveforms presenting high power factor with 230 Vrms and 110 Vrms for RI controller. (c) Current through inductors L_1 and L_3.

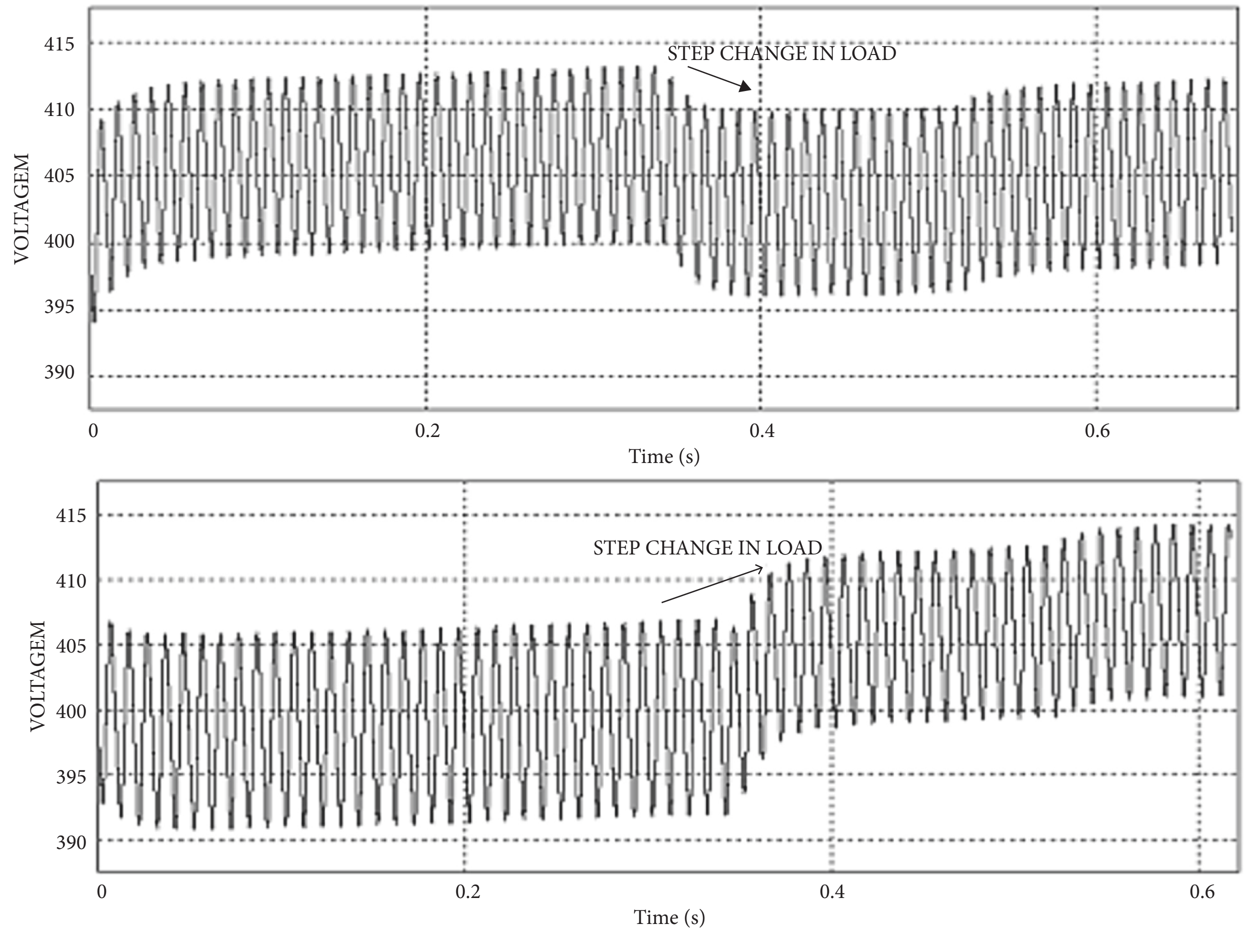
voltage, the input current begins to track the voltage, bringing the power factor closer to 0.9. This is due to the slow external voltage loop, which senses the change in output voltage first and then adjusts the current reference correspondingly.

The duty cycle of the switches is adjusted, resulting in the typical controller's slow response.

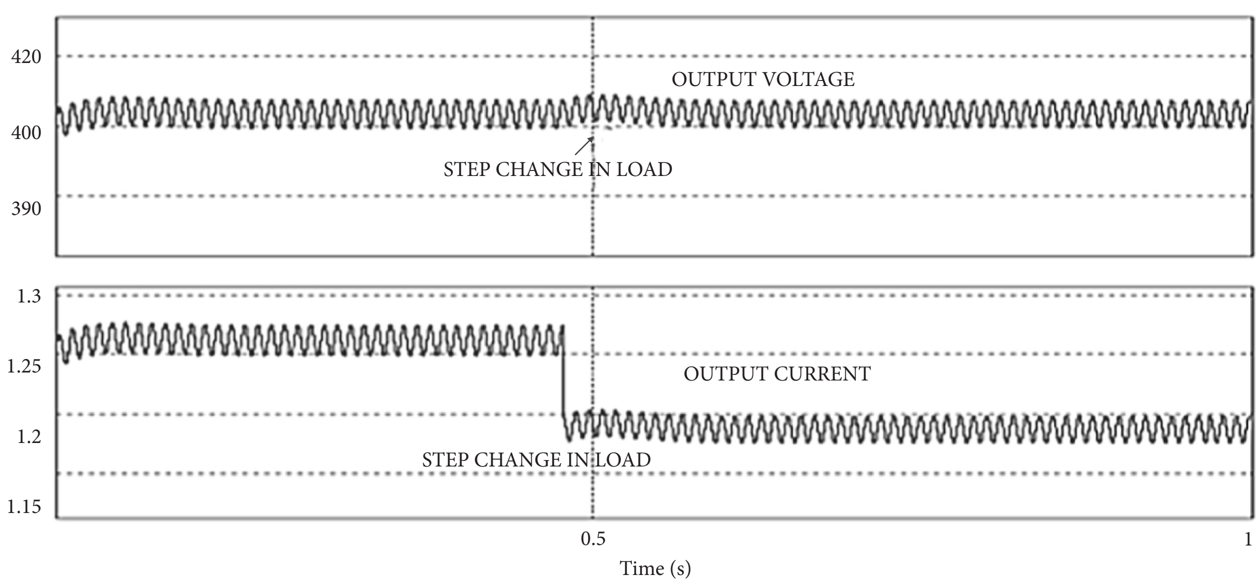
Figure 7(b) illustrates that when the supply voltage is changed from 230 V to 110 V, the power factor (PF) of the input supply is closer to unity. The interleaving inductors reduce the input current ripple in the proposed BLIL converter, and it is shown in Figure 7(b). Gain of PI controller ($K_p = 1$; $K_i = 33.33$) evaluated for PFC with input variations for predicting the performance of RI. It is obvious that the input power factor remains 0.99 for both the cases, in spite of the change in input voltage. Here, the input current traces the instantaneous value of input voltage very fast, and hence, Figure 7 shows a very good power factor with the proposed controller.

The output voltage and output current regulations are observed by introducing a step change in load at $t = 0.38$ s. Figure 8(a) shows the response of the output voltage when a positive and negative step load change is introduced at time $t = 0.38$, respectively. It takes more than 4 cycles ($t > 0.08$ s) to attain the steady-state condition. The output voltage and output current regulations of RI controller are observed by introducing a step change in load at $t = 0.48$ s. A positive step load change (300 W to 350 W) and a negative load change (300 W to 250 W) are introduced at $t = 0.48$ s as shown in Figures 8(b) and 8(c). The controller rejects the disturbances in one switching cycle, which eliminates the overshoot and undershoot of voltage across the device.

For the second-stage converter, the trailing edge gating pulses $vg1$ and $vg2$ with a duty cycle of 37.77% are given to the

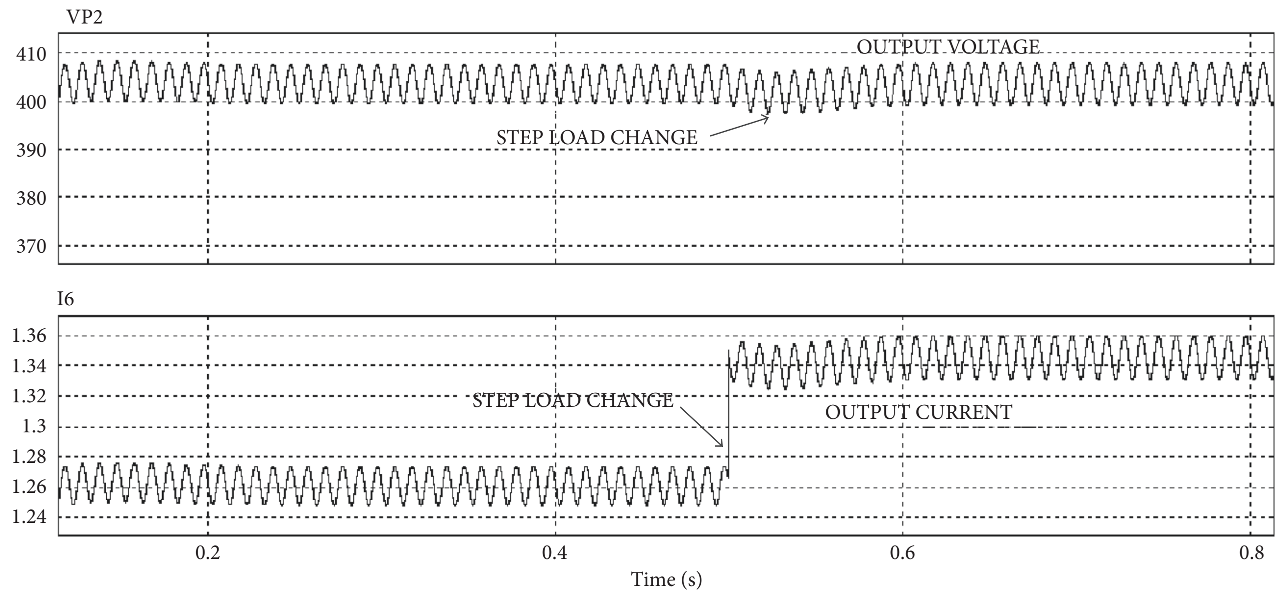


(a)



(b)

Figure 8: Continued.



(c)

Figure 8: (a) Dynamic response of the ACM controller for step change in the load at $t = 0.38$ s. (b) Output voltage and output current for negative step load change at $t = 0.48$ s. (c) Output voltage and output current for a positive step load change at $t = 0.48$ s.

upper pair of switches $M1M_1$ and $M2$. The gating pulses G_4 for $M3$ ($vg3M_3$) and $M4$ ($vg4$) is fixed with 50% duty cycle.

The inverter's ZVS and ZCS turn-on and turnoff, as well as the converter side diodes' ZCS turn-on and turnoff, are accomplished. This rectifies a 300 V voltage and conducts it to the load, where 1 A is the current through the diode.

6. Hardware Results

The prototype feeding the resistive load shown in Figure 9 is designed and tested for 300 W. For the front-end converter, ferrite core inductors of 5.8 mH are connected with 600 V, 99 mΩ Rdson MOSFET for each channel of BLIL boost PFC converter. A 600 V and 6 A silicon carbide diodes are chosen as fast diodes. A resettable integrator PFC controller using IR1150 is used to enhance the PF on the supply side, and UC2895 IC is used as phase shift controller on DC/DC converter. MOSFETs with 600 V, 80 mΩ Rdson, 450 pF parasitic capacitance, are selected as switches for the inverter in the second stage and 400 V/47 μF capacitor for filtering output current ripples.

The converter is tested for (230–110) Vrms under variable load conditions. The waveforms shown in Figures 10(a) and 10(b) are observed on the input side for 230 Vrms and 110 Vrms, respectively, which depicts the input power factor closer to unity. Harmonic spectra of the input current waveform are shown in Figure 10(c), which illustrates that the THD is less than 5% at 110 V input, which is required for PHEV battery chargers to satisfy the IEC standard 61000 3-2 class D requirements.

The inverter gating pulses with duty cycle 37% for switches ($M1$ and $M2$) and 50% for the switches ($M3$ and $M4$) is observed in Figure 11(a). The DC/DC converter waveforms are shown for variable load conditions, focussing that the soft switching can be achieved. The input voltage with 136 V peak to peak for 100 W, appearing across the transformer primary winding, is shown Figure 11(b).

From the waveform, the passive interval (voltage zero instant) in DCM mode can also be observed. ZCS turn-on and turnoff can be attained for the diode ($D3$), which is depicted in Figure 11(c). The DC output voltage 294 V and output current 0.991 A obtained from the diode bridge rectifier is shown in Figure 12(a).

7. Comparison

The proposed topology is compared with the existing front-end converter topology controlled by conventional ACM technique in terms of THD, semiconductor loss distribution, and overall efficacy of the charger system.

The loss distribution for interleaved boost and BLIL boost converter is presented in Figure 12(b) for the following operating conditions: $V_{in} = 230$ V, $V_{out} = 400$ V, switching frequency (fs) = 80 kHz, and output power $P_0 = 300$ W. Conduction losses, switching losses, $1/2CV^2$, and gate charge losses are considered for MOSFET. As SiC diodes are chosen, reverse recovery losses are negligible. The presence of bridge rectifier in interleaved boost converter contributes large portion of loss (approximately 3 W). From the Figure 12(b), total device losses of BLIL converter have lower losses (~3.9 W) when compared to interleaved boost converter. Moreover, the second-stage converter has soft switching achieved for FETs and diodes. Hence, the loss contribution of DC/DC converter is comparatively less compared to conventional DC/DC converter resulting in highly efficient battery charger.

THD of the input current from Figure 13(a) clearly indicates that it complies with IEC standard 61000 3-2 class

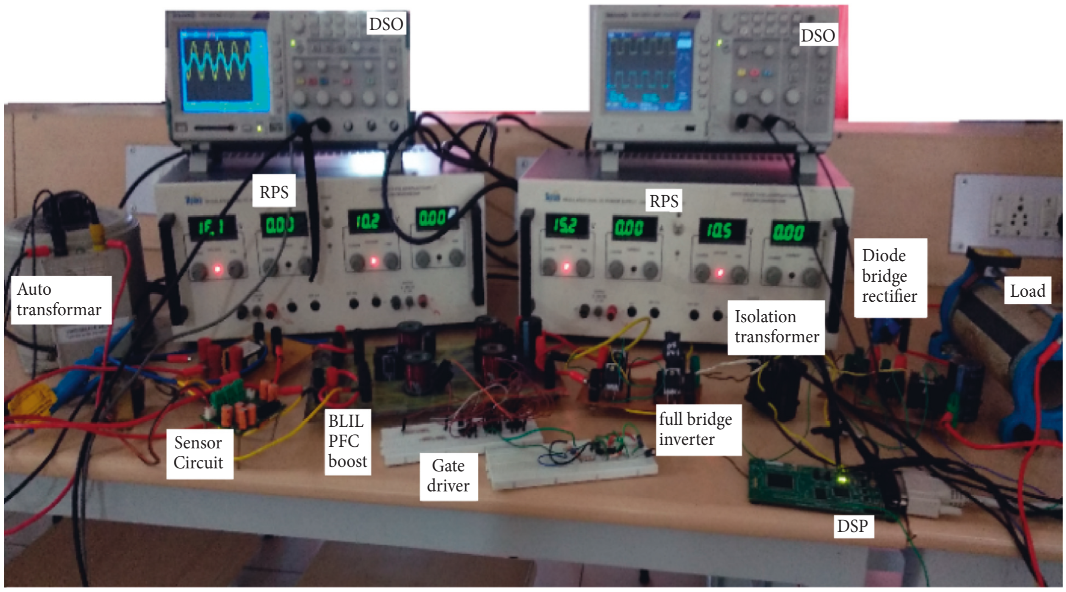


Figure 9: Experimental setup.

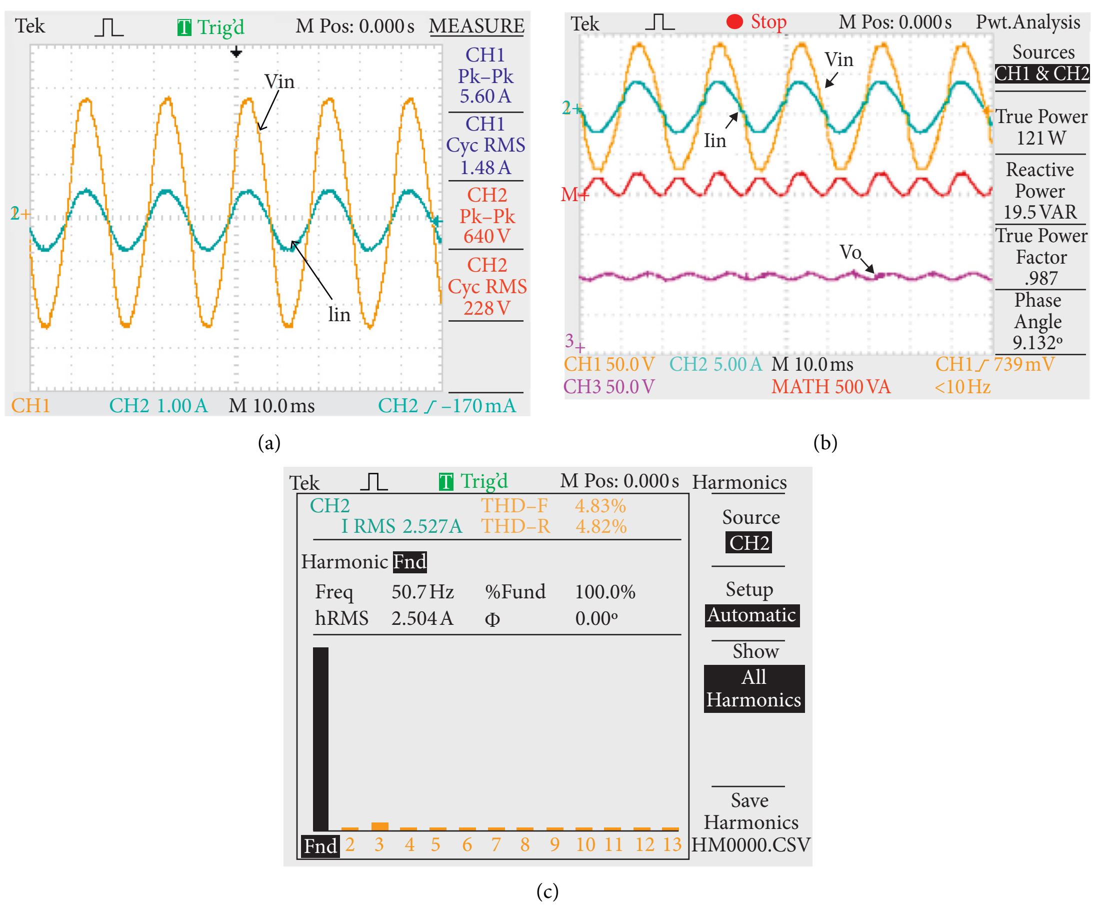
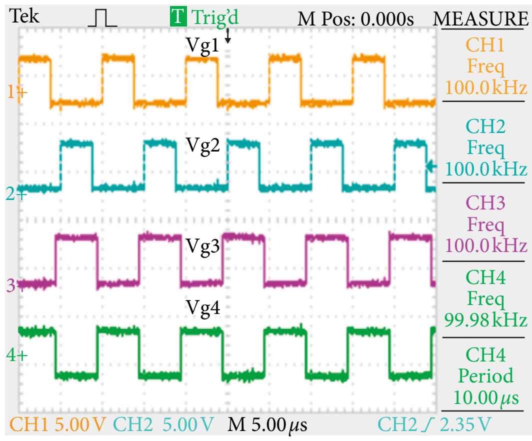
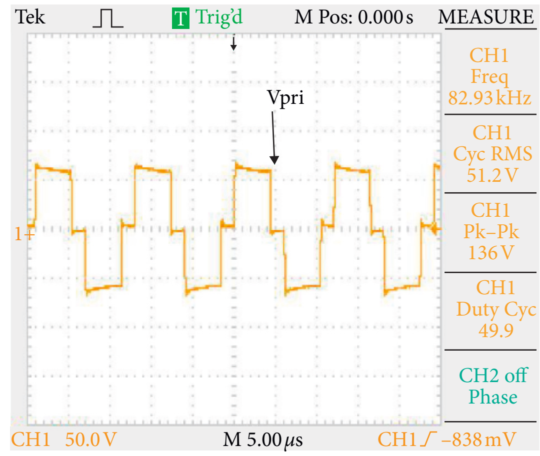


Figure 10: (a) Input voltage and input current waveform of 300 W BLIL boost converter. (b) BLIL boost converter tested for 120 W. (c) THD of input current for 300 W at 110 V input voltage.

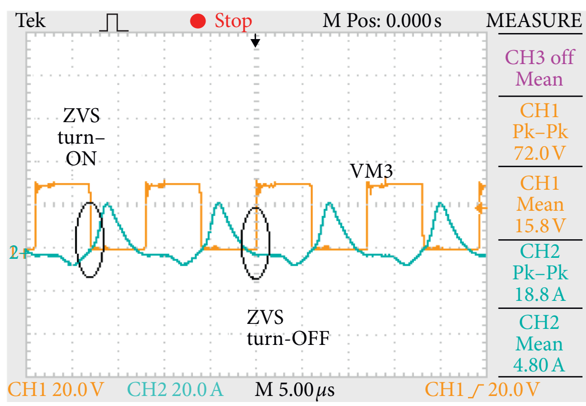
D limit when the converter is operated at 230 V and 110 V at full load condition. Figure 13(b) is the comparison graph of traditional interleaved and BLIL boost converter as front-end converter for variable output power. The graph implies that the peak efficiency of the charger with BLIL PFC converter is 96.5%, whereas the traditional interleaved converter efficiency is 93%. The comparison of the charger setup with respect to control technique is analysed and



(a)

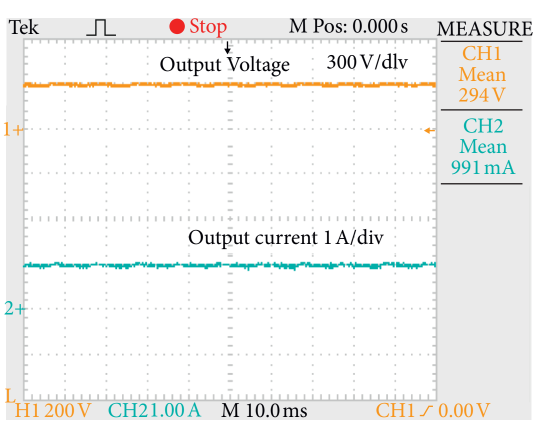


(b)

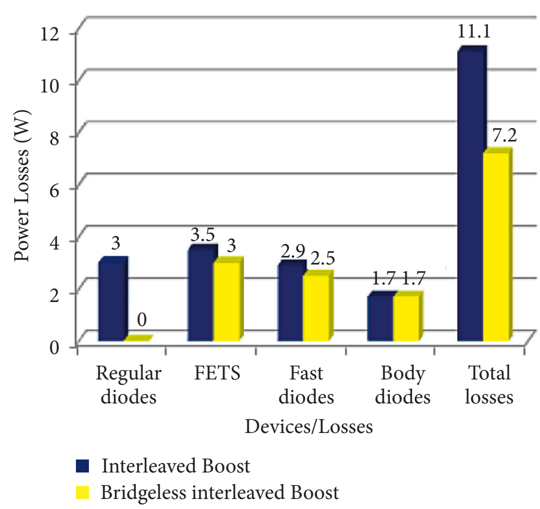


(c)

Figure 11: (a) Gating pulses to Switches $M1(Vg1)$, $M2(Vg2)$, $M3(Vg3)$, and $M4(Vg4)$, (b) Transformer primary voltage for 100 W, and (c) ZCS turn-on and turnoff of diodes for 180 W.

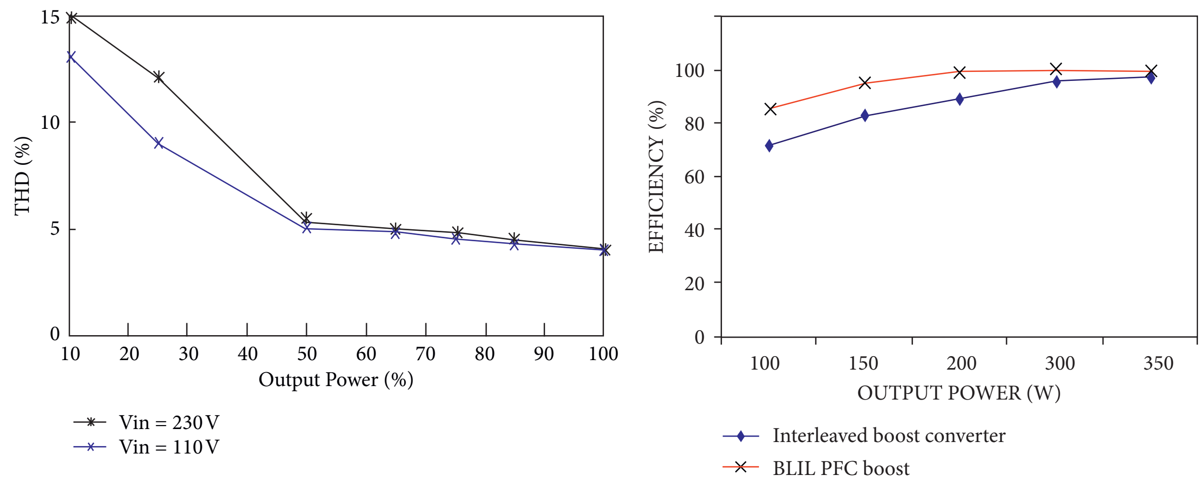


(a)



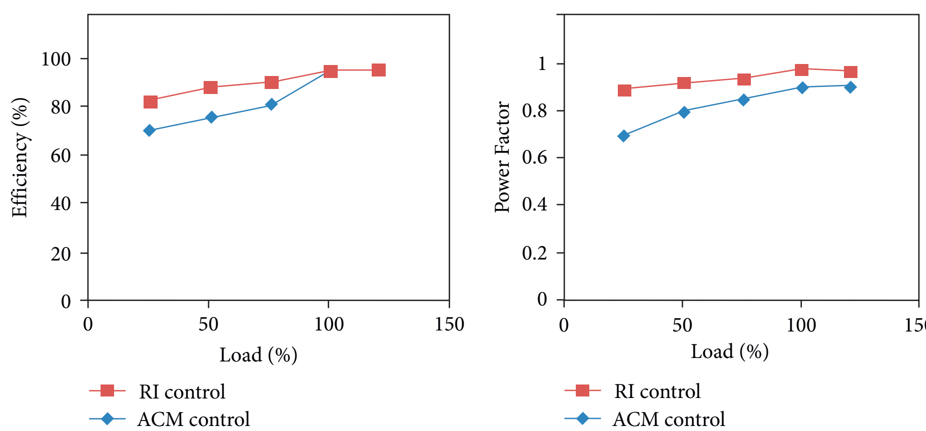
(b)

Figure 12: (a) Output voltage and output current waveform for 300 W. (b) Device loss distribution for interleaved boost and BLIL boost converter for 300 W prototype.



(a) (b)

Figure 13: (a) Total harmonic distortion vs output power (%) for $V_{in} = 110$ V and $V_{in} = 230$ V. (b) Efficacy of the converter under variable load condition.



(a) (b)

Figure 14: (a) Efficacy vs load power (%). (b) Power factor vs load (%).

shown in Figures 14(a) and 14(b). From the graph, it is inferred that the efficacy and power factor of the front-end converter of the charger are high for RI control than ACM control.

8. Conclusion

A high-performance two-stage converter topology for PHEV battery charger with improved PFC rectifier as front-end and a high-frequency ZVS-ZCS DC/DC converter as the second stage has been discussed in this paper. The operation, design considerations, and performance comparison with the traditional two-stage approach are presented. A non-linear RI control technique is implemented for the front-end converter, which corrects power factor closer to unity in one switching cycle at variable load powers. THD of the input current is less than 5%, which is compliant with the IEC 61000 3-2 standard. For PFC converter and DC/DC converter, respectively, the proposed charger achieves a peak efficiency of 96.5% at 80 kHz and 100 kHz switching frequency. It operates for a wide output load variation. Thus, the overall designated charger unit achieves an efficiency of 3.5% higher than the conventional battery charger unit.

Data Availability

The data used to support the findings of this study are included in the article. Should further data or information be required, these are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Cooperation Modes between Competing Manufacturers in EV Supply Chain with Innovation-Driven Common Supplier

Bin Liu and Ruoying Huang

Business School, University of Shanghai for Science and Technology, Shanghai 200093, China

Correspondence should be addressed to Bin Liu; liubhnau@163.com

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The competition and cooperation between automobile manufacturers and battery enterprises are an important topic concerned by electric vehicle supply chain management. This paper investigates the cooperation modes between competing manufacturers in the EV (electric vehicle) supply chain, under which the common supplier launches the innovation of the key component of EV to meet the demand of two manufacturers. Three cooperation modes between manufacturers, full cooperation, partial cooperation, and noncooperation, are established to depict the pricing decisions by the Stackelberg game. We find out that, when competition degree is small, it is more profitable to choose partial cooperation, while it is more advantageous to choose full cooperation when competition degree is high, and the manufacturer's basic market demand is relatively small. Therefore, it is always preferred for the common supplier to expect noncooperation between manufacturers. Under the background that basic market demand ratio changes with competition degree between markets, it could be better for the whole supply chain when without cooperation or partial cooperation depended on the supplier power while it could be better for customers when full cooperation or partial cooperation depended on the competition degree between manufacturers.

1. Introduction

Facing the great challenges of transportation energy and environmental problems, new energy vehicles characterized by energy diversification, clean emission, and fuel conservation are developing rapidly all over the world. At present, international auto giants have accelerated the promotion of electric vehicle strategy. Batteries, as the most important component of electric vehicles, become the focus of the competition among global automotive component suppliers, and all companies want to occupy a high position in the new energy vehicle market. In the electric vehicle battery market, not only do battery suppliers begin to carry out technological innovation but also automobile manufacturers are actively innovating. For example, a well-known battery supplier is striving for orders from global automobile manufacturers; on the other hand, some automobile manufacturers intend to master the core battery technology by themselves. For example, Tesla, the main customer of Panasonic batteries, plans to develop and produce the required batteries by itself.

In practice, there is usually a cooperative relationship between a common supplier and multiple competitive manufacturers. For example, Huawei and Xiaomi will jointly sign a contract on CPU (central processing unit) with Qualcomm Snapdragon, and BMW and Jaguar will use the same chassis supplier. In this case, the products of downstream competitive manufacturers will compete with each other in the market, but all manufacturers who sign a contract with a common supplier will have common benefits. How to decide the cooperation mode for competing manufacturers facing the common supplier is a problem worthy of attention. This paper studies this problem and provides some meaningful guidance for the operation and management of the supply chain.

The rest of this paper is organized as follows: Section 2 presents the related literature, and section 3 discusses the research assumptions and basic models. Then, section 4 is three cooperation models between competing manufacturers, and their comparison and equilibrium analysis are in section 5. Finally, section 6 is the results and further research.

2. Related Literature

Innovation is always an important issue concerned by academia and industry. From the perspective of supply chain member innovation, this paper mainly focuses on two research fields. One research area includes supplier innovation in the supply chain, and supplier innovation can be divided into active innovation or buyer incentive supplier innovation. Sometimes, suppliers will take the initiative to improve product quality and technical level. Similarly, the buyer requires the supplier to meet the demand for product improvement. With the increase of global innovation outsourcing and the rising trend of open innovation, suppliers play a very important role in the global supply chain. In terms of supplier competition, Qi et al. [1] take a dual-channel supply chain composed of two upstream suppliers and one downstream manufacturer as the background. Considering the wholesale price factor, Qi et al. [1] analyze the optimal strategy for manufacturers to select suppliers when there is competition among suppliers. Li and Wan [2] investigate the impact of information asymmetry and information symmetry on supplier investment cost.

In the existing literature, supply chain competition is generally studied from three aspects: manufacturer competition, supplier competition, and considering the competition among multiple chains. For example, manufacturers tend to compete in terms of the product price, the service, and the quality. Xiang et al. [3] focus on the situation under which there is recycling competition in the process of remanufacturing waste products obtained by multiple manufacturers in the market, using optimization theory and noncooperative game theory, and discuss the impact of competition among remanufacturers and remanufacturing cost on the relationship between supply chain members. Zhu and Zhou [4] conduct research around the new energy vehicle industry related to the hot topic of government subsidies and analyze the competitive relationship between component manufacturers and remanufacturers by establishing a game model. Özdemir et al. [5] study the manufacturer's remanufacturing decision in the environment of a legislative disposal fee. Wu et al. [6] consider the competition between manufacturers and remanufacturers and investigate the manufacturer's strategic dilemma when determining the degree of disassembly. Subramanian et al. [7] extend the classic component commonality decision to consider remanufacturing operated by manufacturers or remanufacturers. The investment in component commonality can be regarded as an investment in reducing remanufacturing costs. Their analysis identifies the conditions under which generic decisions could be reversed by remanufacturing. Li et al. [8] investigate the impact of remanufacturing on product design, especially the quality of new products. They find that remanufacturing prompted monopolists to provide new products of higher quality.

Recent operations management literature studies issues surrounding the green technology innovation market (such as [9–14]), including environmental taxes and subsidies, policy issues, strategic decision-making, production decisions, and supply chain performance. In terms of research related to supply chain management innovation, Li and Zhu [15] depict the disadvantages of product positioning strategy and the advantages of product platform strategy when product innovation faces fierce competition and encourages managers to expand their ideas of technology R&D and product innovation. Yu and Li [16] probe into the optimal decision-making of channel members under different innovation strategies under the dominant and nondominant position of suppliers by establishing the product innovation model of suppliers and retailers. Huo et al. [17] find that product-oriented service transformation and incremental innovation have no significant complementary effect on the high-quality development of manufacturing enterprises, which is helpful to solve the problem of enterprise product innovation strategy selection. Ni and Zhao [18] establish a game theory model to find out the impact of vertical competition and cooperation on product innovation in the supply chain and compare the innovation investment level and the optimal decisions of upstream suppliers and downstream retailers under vertical competition and cooperation. Guoyin et al. [19] build an incomplete information dynamic game model between enterprises and consumers, investigate how enterprises motivate consumers through the innovation degree of new products, and decide whether to produce and sell products through the information fed back by consumers.

In the research field of alliance cooperation behavior in supply chain and operation management, Zhao et al. [20] investigate the collision behavior of two manufacturers in the retailer-led supply chain, and undoubtedly, manufacturers collude to make shelf space and pricing decisions to maximize their total profits. The cost difference is the key factor affecting their collusion decision-making, which will only pose an unreliable threat to retailers. Collusion is a nonprofit strategy, which involves the horizontal competition of manufacturers when there are large differences in costs. Melkonyan et al. [21] discuss the impact of collusion, which distinguishes the results between Bertrand and Cournot competition. They find out that virtual bargaining can make participants collude and obtain higher profits; in contrast, it does not make much sense in the Cournot competition. Chen et al. [22] study the problem of responsible procurement under the collusion of suppliers and auditors. An effective contract strategy is proposed to reduce collusion and eliminate the impact of screening errors and social efficiency loss caused by supplier audit collusion. In the aviation supply chain, there are also relevant studies on alliance cooperation [23–25], which mainly analyze the cooperation motivation between airlines and airports.

In addition, in the past few decades, there has been a lot of research on supply chain innovation. Wong and Ngai [26] believe that supply chain innovation is usually the stage of the supplier, manufacturer, and "supplier plus manufacturer." They propose that the innovation can be divided into three categories from the perspective of organizational behavior: market-oriented innovation activities, logistics-oriented innovation activities, and technology-based innovation activities. According to the definition of innovation, Gao et al. [27] propose six types of innovation, namely product innovation, process innovation, technological innovation, organizational innovation, marketing innovation, and resource allocation innovation. The above scholars have classified innovation from the macro level. In addition, Bruce [28] proposes that from the perspective of innovation-driven, the innovation can be divided into technology-driven innovation and market-driven innovation.

The product innovation activities considered in this paper are mainly based on the improvement of product quality level. By establishing the model, taking the product quality level and the service quality level of manufacturers and retailers into account in the supply chain, and studying the results under different game situations, it is concluded that the adjustment speed of the service quality level of manufacturers and retailers is too fast, which will eventually bring losses to the whole supply chain.

This paper will investigate how competitive manufacturers can negotiate with suppliers in the face of three different modes: full cooperation (manufacturers as an alliance, the same wholesale price, and the same sale prices), partial cooperation (unified wholesale price and different sale prices for manufacturers), and noncooperation (different wholesale prices and different sale prices), and whether the alliance between manufacturers can gain advantages in negotiations with suppliers. Furthermore, which operation mode preferred for suppliers is discussed.

3. Research Assumptions and Basic Model

This paper discusses a vehicle supply chain system consisting of the common supplier and competing manufacturers. Manufacturers have the same product types and compete in the product market (manufacturers have the same technology). From the perspective of the vertical structure of the supply chain, the supply chain structure of one supplier and two manufacturers allows the shared supplier to have a higher right to speak, and a single manufacturer is at a disadvantage when negotiating with it. So, at this time whether downstream manufacturers cooperate to enhance their bargaining power with suppliers, such as Ford and Jaguar Land Rover jointly invest in innovation in battery suppliers, while Tesla and Volkswagen are negotiating with Panasonic battery suppliers, respectively. Based on this, this paper studies the impact of three different interaction behaviors of manufacturers on the decision-making of supply chain members. The common suppliers take the initiative to innovate and provide competitive manufacturers with key components required for vehicle production. When manufacturers sign agreements and cooperate with suppliers, they can consider how to cope with their competitors. The cooperation modes between competing manufacturers can be divided into three ways, full cooperation, partial cooperation, and noncooperation. Full cooperation of manufacturers means that manufacturers form alliances in the downstream to determine the prices of products to be sold; partial cooperation means that manufacturers maximize their overall profits in the downstream market, but the products compete in the market they face; noncooperation means that manufacturers use their own profits. Maximize is the principle and compete in the product market.

In the supply chain composed of one supplier and two manufacturers, the supplier has a higher voice, and the negotiation with the manufacturer alliance will lose their position. It is worth considering whether downstream manufacturers cooperate to enhance their bargaining power with suppliers or negotiate with suppliers alone. This paper analyzes the impact of manufacturers' interactive behavior on supply chain members' decision-making. The idea for this part comes from the literature [29].

According to the decision-making order, the supplier first determines its wholesale price and innovation level, and the manufacturer determines its cooperation V mode and then determines the sales price. We call the manufacturer's full cooperation case *C*, partial cooperation case *S*, and noncooperation case *N*, respectively. We will build models for decision analysis. The following parameters will be used in this paper, and their meanings are shown in Table 1.

We assume that the manufacturers' basic demand is A_i when $e = 0$, where e is the innovation level. If the common supplier determines its innovation level, the basic demand of the manufacturer i becomes $a_i\,(a_i = A_i + e)$. Furthermore, the competition degree between markets is $\theta\,(\theta < 1)$. We also assume that $C(e_s) = \varphi_s e_s^2$ alike literature [30, 31], and for simpler, the coefficient $\varphi_s = 1$. Through numerical example analysis, these assumptions do not affect the results.

Referring to the market demand model of Ingene [32, 33], here, the market demand function and consumption utility function of manufacturer i are as follows:

$$D_i = \frac{a_i - \theta * a_{3-i} - p_i + \theta * p_{3-i}}{1-\theta^2}, \quad (i = 1, 2),$$
$$U \equiv \sum_{i=1,2}\left(\alpha_i D_i - \frac{D_i^2}{2}\right) - \theta D_1 D_2 - \sum_{i=1,2} p_i D_i. \tag{1}$$

To express the potential asymmetry between the markets confronted by two chains, here, we define $\Omega \equiv A_1/A_2$. We also refer to Ω as the base demand ratio. If $\Omega > 1$, the chain 1's initial base demand is larger than that of chain 2's. This has been discussed in it [34].

4. Cooperation Models between Manufacturers: Three Cooperation Scenarios

4.1. Scenarios C: Full Cooperation between Manufacturers. Under the scenario of full cooperation between manufacturers, the supplier gives the same wholesale price to two manufacturers. The manufacturers ally with the downstream

Table 1: Definitions of model parameters.

Parameters	Definition
A_i	Basic demand in the market i, $i = 1, 2$
a_i	Basic demand in market i when $e \neq 0$时, $a_i = A_i + e$; $i = 1, 2$
Ω	Basic market demand ratio, $\Omega = A_1/A_2$
e	Supplier innovation level
η	Manufacturer's share of innovation cost
D_i	Demand in the market i, $i = 1, 2$
θ	Competition degree between markets
U	Consumer utility
w	Wholesale price per unit
p_i	Selling price of manufacturer i per unit, $i = 1, 2$
$C(e_s)$	Supplier innovation costs
π_{mi}	Profit of manufacturer i, $i = 1, 2$
π_s	Supplier's profit

to determine the price of products. Taking this scenario as the benchmark, the decision-making order of both parties under this scenario is the supplier actively carries out upstream innovation and determines the innovation level and wholesale price; after learning that the supplier is innovating, the manufacturer chooses to fully cooperate in the sales of the final product and determine the price of the product. The demand function is

$$D_i^C = \frac{\left(\alpha_i - \theta * \alpha_{3-i} - p^C + \theta * p^C\right)}{\left(1 - \theta^2\right)}. \tag{2}$$

The profit functions of suppliers and manufacturers are

$$\pi_S^C = w^C * \left(D_2^C + D_2^C\right) - e_1^2, \tag{3}$$

$$\begin{aligned} \pi_{m1}^C &= D_1^C * \left(p^C - w^C\right), \\ \pi_{m2}^C &= D_2^C * \left(p^C - w^C\right). \end{aligned} \tag{4}$$

Taking the reverse order solution method, the manufacturer's profit function is a concave function on price p. When the manufacturer fully cooperates, the two strategic alliance manufacturers determine the product price p based on the principle of maximizing their overall profit. We can get the selling price $p^C = 1/4(A_1 + A_2 + 2(w^C + e_1))$ given the wholesale price w^C. And then, to substitute p^C into formula (3), we can get the profit of supplier $\pi_s^C = w^C(A_1 + A_2 - 2w^C) + 2w^C e_1 - 2(1+\theta)e_1^2/2(1+\theta)$.

By the same method, we can prove the profit of supplier, π_s, is joint concave on (w, e). So, we can get the optimal wholesale price and innovation level, respectively, $w^{C^*} = (1+\theta)(A_1 + A_2)/3 + 4\theta$ and $e_1^* = A_1 + A_2/6 + 8\theta$ according to the first-order necessary condition of π_s. Furthermore, we can get the optimal selling price $p^{C^*} = 3(1+\theta)(A_1 + A_2)/6 + 8\theta$ and then gain the optimal profits of all members and the whole supply chain as follows:

$$\begin{aligned} \pi_{m1}^{C^*} &= \frac{(1+\theta)\left(A_1 + A_2\right)\left((4+3\theta)A_1 - (2+5\theta)A_2\right)}{4(1-\theta)(3+4\theta)^2}, \\ \pi_{m2}^{C^*} &= \frac{(1+\theta)\left(A_1 + A_2\right)\left((4+3\theta)A_2 - (2+5\theta)A_1\right)}{4(1-\theta)(3+4\theta)^2}, \\ \pi_s^{C^*} &= \frac{\left(A_1 + A_2\right)^2}{4(3+4\theta)}. \end{aligned} \tag{5}$$

4.2. Scenarios S: Partial Cooperation between Manufacturers. In the manufacturer's partial cooperative scenario, although the supplier will adopt a unified wholesale price, the manufacturer will set their product prices based on the principle of maximizing their profits and compete with their products in the market, such as Ford and Jaguar Land Rover. The decision-making order of both parties is that the supplier actively carries out upstream innovation and determines the innovation level and wholesale price. After learning that the supplier carries out innovation, the manufacturer chooses partial cooperation to sell the final products and determine the price of its products, respectively. Here, the demand function is

$$D_i^S = \frac{\alpha_i - \theta * \alpha_{3-i} - p_i^S + \theta * p_{3-i}^S}{1 - \theta^2}. \tag{6}$$

The profit functions of supplier and manufacturers are

$$\begin{aligned} \pi_s^S &= w^S * \left(D_1^S + D_2^S\right) - e_2^2, \\ \pi_{m1}^S &= D_1^S * \left(p_1^S - w^S\right), \\ \pi_{m2}^S &= D_2^S * \left(p_2^S - w^S\right). \end{aligned} \tag{7}$$

By the same method, we can prove the supplier's profit function π_s^S is joint concave on (w^S, e_2). So, we can get the optimal wholesale price and innovation level $w^{S^*} = (2-\theta)(1+\theta)(A_1+A_2)/6+4(1-\theta)\theta$ and $e_2^* = A_1 + A_2/6+4(1-\theta)\theta$. And then, the optimal selling prices are $p_1^{S^*} = (1+\theta)((9+\theta(1-4\theta))A_1+3(1-\theta)A_2)/2(2+\theta)(3+2(1-\theta)\theta)$ and $p_2^{S^*} = (1+\theta)((9+\theta\ \ (1-4\theta))A_1+3(1-\theta)A_1)/\ \ 2(2+\theta)(3+2(1-\theta)\theta)$.

The optimal profits of all members and the whole supply chain are as follows:

$$\begin{aligned}
\pi_{m1}^{S^*} &= \frac{(1+\theta)((5+\theta(1-3\theta))A_1-(1+(3-\theta)\theta)A_2)^2}{4(1-\theta)(2+\theta)^2(3+2(1-\ \theta)\theta)^2},\\
\pi_{m2}^{S^*} &= \frac{(1+\theta)\left(\left(5+\theta-3\theta^2\right)A_2-(1+(3-\theta)\theta)A_1\right)^2}{4(1-\theta)(2+\theta)^2(3+2(1-\ \theta)\theta)^2},\\
\pi_s^{S^*} &= \frac{\left(A_1+A_2\right)^2}{12+8(1-\theta)\theta}.
\end{aligned} \tag{8}$$

4.3. Scenarios N: Noncooperation between Manufacturers. Under the manufacturer's noncooperation scenario, the common supplier and manufacturers compete in the product market based on the principle of maximizing their respective profits, such as Xiaomi and Huawei. The decision-making order of both parties is that the supplier actively carries out upstream innovation and determines the innovation level and the wholesale price to different manufacturers, and the manufacturers choose not to cooperate after learning that the supplier carries out innovation, sells the final products, and determines the price of their products, respectively. Here, the demand function is

$$D_i^N = \frac{\alpha_i - \theta^* \alpha_{3-i} - p_i^N + \theta^* p_{3-i}^N}{1-\theta^2}. \tag{9}$$

The profit functions of the common supplier and manufacturers are listed as follows:

$$\begin{aligned}
\pi_s^N &= w_1^N * D_1^N + w_2^N * D_2^N - e_3^2,\\
\pi_{m1}^N &= D_1^N * \left(p_1^N - w_1^N\right),\\
\pi_{m2}^N &= D_2^N * \left(p_2^N - w_2^N\right).
\end{aligned} \tag{10}$$

By the similar method, we can prove the common supplier's profit function π_s^N is joint concave on (w_1^N, w_2^N, e_3) by the third-order Hessian matrix analysis. Then, we can gain the optimal wholesale price and innovation level are $w_1^{N^*} = (7+4(1-\theta))\theta A_1 + A_2/12 + 8(1-\theta)\theta$, $w_2^{N*} = A_1 + (7+4(1-\theta)\theta)A_2/12+8\ (1-\theta)\theta$, and $e_3^* = A_1 + A_2/6+4(1-\theta)\theta$. Furthermore, the optimal selling prices of production in markets are as follows: ${p_1}^{N*} = (21+2\theta(11-4\theta(1+\theta)))A_1 + (3-2\theta-4\theta^2)A_2/4\ \ (2+\theta)(3+2(1-\theta)\theta)$ and ${p_2}^{N*} = (21+2\theta(11-4\theta\ \ (1+\theta)))A_2 + (3-2\theta-4\theta^2)A_1/4(2+\theta)(3+2(1+\theta)\theta)$.

The optimal profits of all members and the whole supply chain are as follows:

$$\begin{aligned}
\pi_{m1}^{N^*} &= \frac{(1+\theta)\left(\left(7-4\theta^2\right)A_1+(1-4\theta)A_2\right)^2}{16(1-\theta)(2+\theta)^2(3+2(1-\ \theta)\theta)^2},\\
\pi_{m2}^{N^*} &= \frac{(1+\theta)\left(\left(7-4\theta^2\right)A_1+(1-4\theta)A_1\right)^2}{16(1-\theta)(2+\theta)^2(3+2(1-\ \theta)\theta)^2},\\
\pi_s^{N^*} &= \frac{\left(7-4\theta^2\right)A_1^2+2(1-4\theta)A_1A_2+\left(7-4\theta^2\right)A_2^2}{8\left(6+\theta-9\theta^2+2\theta^4\right)}.
\end{aligned} \tag{11}$$

5. Models Comparison and Equilibrium Analysis

By solving the models of full cooperation, partial cooperation, and noncooperation, the optimal decisions and maximum profits of manufacturers and suppliers under different scenarios are obtained. This section will compare and analyze the maximum profit under three different scenarios to get relevant conclusions.

Proposition 1. *Given innovation by the common supplier, for manufacturer 1's profit under three scenarios, we can get the following.*

(1) Full cooperation is preferred for manufacturer 1 under the feasible zone, $\widehat{\Omega}_{m1}^{C-S} < \Omega < \overline{\Omega}^C$ due to $\pi_{m1}^C > \pi_{m1}^S > \pi_{m1}^N$

(2) Partial cooperation is preferred for manufacturer 1 under the zone $\widehat{\Omega}_{m1}^{C-N} < \Omega < \overline{\Omega}^C$ and $\widehat{\Omega}_{m1}^{C-S} < \Omega < \overline{\Omega}^C$ due to $\pi_{m1}^S > \pi_{m1}^C > \pi_{m1}^N$

(3) Noncooperation is preferred for manufacture 1 under $\underline{\Omega}^C < \Omega < \widehat{\Omega}_{m1}^{C-N}$ due to $\pi_{m1}^N > \pi_{m1}^S > \pi_{m1}^C$

From Proposition 1, we can find out that for manufacturers, when their basic market demand is close to their competitors and their products are highly competitive, manufacturers will choose full cooperation, which can form a strategic alliance and reduce the losses caused by competition; when the products of two manufacturers are less competitive in the market, as long as the basic market demand of the manufacturer is greater than that of the competitor, it will choose partial cooperation. At this time, it has a certain voice in the market, so choosing partial cooperation to set its product sales price alone is conducive to obtaining more profits from the market; when its basic market demand is relatively small compared with its competitors, regardless of the degree of market competition of products, it will choose not to cooperate and sign a separate contract with suppliers to ensure its voice in negotiation with suppliers, so that it can obtain more profits. Figure 1 illustrates the above results.

Proposition 2. *Given innovation by the common supplier, for manufacturer 2's profit under three scenarios, we can get the following.*

(1) Full cooperation is preferred for manufacturer 2 under the feasible zone, $\underline{\Omega}^C < \Omega < \widehat{\Omega}_{m2}^{C-S}$ due to $\pi_{m2}^C > \pi_{m2}^S > \pi_{m2}^N$

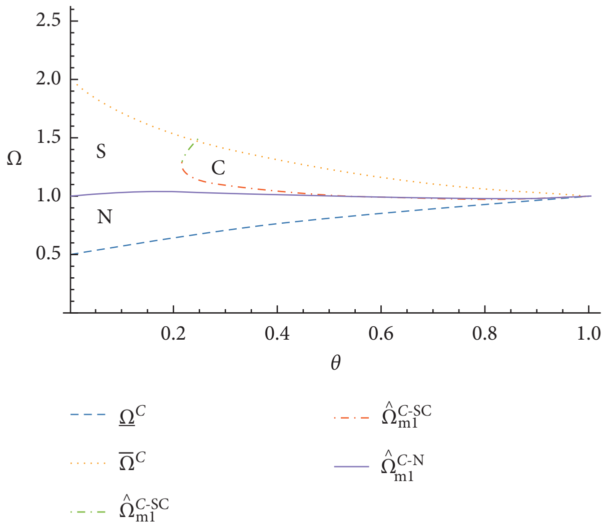

Figure 1: Cooperation mode choice for manufacturer 1.

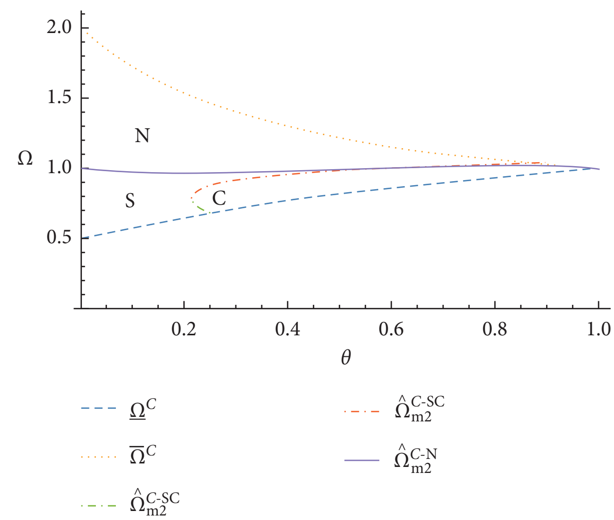

Figure 2: Cooperation mode choice for manufacture 2.

(2) Partial cooperation is preferred for manufacturer 2 under the zone $\underline{\Omega}^C < \Omega < \widehat{\Omega}_{m2}^{C-N}$ *and* $\widehat{\Omega}_{m2}^{C-S} < \Omega < \widehat{\Omega}_{m2}^{C-N}$ *due to* $\pi_{m2}^{SC} > \pi_{m2}^{C} > \pi_{m2}^{N}$

(3) Noncooperation is preferred for manufacture 2 under the zone $\widehat{\Omega}_{m2}^{C-N} < \Omega < \overline{\Omega}^C$ *due to* $\pi_{m2}^{N} > \pi_{m2}^{S} > \pi_{m2}^{C}$

From Proposition 2, it can be seen that for manufacturers, when their basic market demand is close to that of their competitors, and their products have high substitutability in the market; that is, there is great competition, and manufacturers will choose full cooperation, which can form a strategic alliance and reduce the losses caused by competition. In this case, the manufacturer and the competitor will reach an agreement to form a strategic alliance to sign a contract with the supplier; when the substitutability of two manufacturers' products is low in the market, that is, the competition is very small. As long as its basic market demand is greater than that of the manufacturer, it will choose partial cooperation. At this time, it has a certain voice in the market. Therefore, choosing partial cooperation to set its own product sales price alone is conducive to obtaining more profits from the market. When its basic market demand is relatively small compared with that of the manufacturer, no matter whether the product is more or less substitutable in the market; that is, competition degree is large or small, and it will choose noncooperation to sign a contract with the supplier alone, so as to ensure its voice in negotiation with the supplier and ensure that it can obtain more profits. Figure 2 illustrates the above results, and it is easy to find that Figure 2 is symmetrical with Figure 1.

From Propositions 1 and 2, we can get the following inference.

Inference 1. For the manufacturers, it is preferred to choose full cooperation with the common supplier if the basic market demand of two manufacturers is similar, and their products are highly competitive, while to choose noncooperation if there is an obvious gap between the basic market demand of the two manufacturers and competition degree is low.

Inference 1 implies that only two equilibriums occur, and partial cooperation will not be chosen because when their basic market demand is low, choosing partial cooperation will only be beneficial to competitors, so they will not choose partial cooperation mode.

Proposition 3. *Facing the manufacturers' choice, the common supplier's innovation level* $e_3 > e_2 = e_1$*, and it is preferred to choose noncooperation under the zone* $\underline{\Omega}^C < \Omega < \overline{\Omega}^C$ *due to* $\pi_S^N > \pi_S^S > \pi_S^C$*.*

From Proposition 3, we can find that for the common supplier, the innovation level is the same under the scenarios of full cooperation and partial cooperation with manufacturers; that is, when the manufacturer obtains products at the same wholesale price, it will choose the same innovation level to reduce the innovation cost; when the manufacturer does not cooperate, the wholesale price is different. Under the competition of the manufacturer, the supplier is willing to improve the innovation level and improve the competitiveness of the product, to obtain more profits. Figure 3 illustrates the above results well.

Proposition 4. *For the whole supply chain, noncooperation is preferred under the zone* $\widehat{\Omega}^{S-N} < \Omega < \overline{\Omega}^C$ *due to* $\pi^N > \pi^S > \pi^C$*, while partial cooperation is preferred under the zone* $\underline{\Omega}^C < \Omega < \widehat{\Omega}^{S-N}$ *due to* $\pi^S > \pi^N > \pi^C$*.*

From Proposition 4, we can find that for the whole supply chain, manufacturers will not choose to cooperate completely. This is because, under full cooperation, manufacturers are strategic alliances in downstream. When facing the market, the sales price is the same, and there is no motivation to strive for more profits. At this time, the innovation level of suppliers facing the downstream strategic alliance will also be reduced, which makes the overall profit the lowest; when the basic market demand of the whole supply chain is small, the manufacturer's partial cooperation strategy will be selected. At this time, for the whole supply chain, it needs to expand the

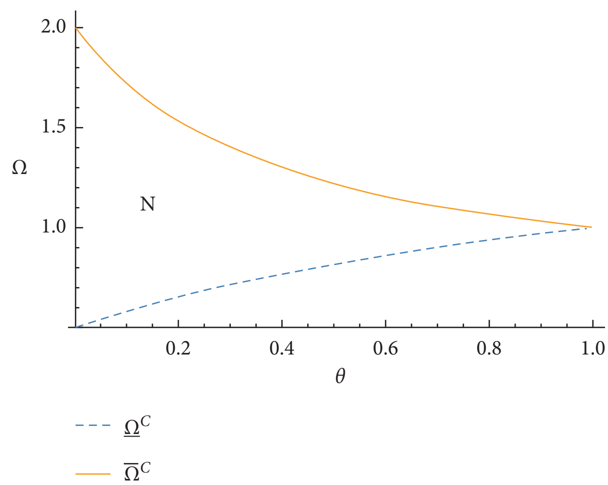

Figure 3: Cooperation mode choice for the common supplier.

basic market demand to improve the product sales to obtain more revenue. Therefore, the downstream manufacturers should avoid the loss of overall profits caused by complete competition; when the basic market demand of the whole supply chain is large, manufacturers will choose noncooperation. At this time, products have been recognized by consumers in the market, so manufacturers need to make more efforts through competition to make the market demand larger. When manufacturers compete, suppliers will also have more power to improve the innovation level and to make the whole supply chain obtain more profits. Figure 4 illustrates the above results well.

Proposition 5. *For the consumers, partial cooperation is preferred under the zone* $\underline{\Omega}_U^{C-N} < \Omega < \overline{\Omega}_U^{C-N}$ *and* $\underline{\Omega}^C < \Omega < \overline{\Omega}^C$ *due to* $U^S > U^N > U^C$, *while full cooperation is preferred under the zone* $\overline{\Omega}_U^{C-N} < \Omega < \overline{\Omega}^C$ 且 $\underline{\Omega}^C < \Omega < \underline{\Omega}_U^{C-N}$ *due to* $U^C > U^S > U^N$.

From Proposition 5, we can find that for consumers, when the basic market demand of two manufacturers is not much different, that is, the market share of their products is basically the same, and they will choose the manufacturer's partial cooperative scenario. At this time, there is both cooperation and competition between manufacturers to maximize the utility of consumers, and consumers will get more benefits; when there is a large difference between the basic market demand of two manufacturers, that is, one manufacturer's products occupy most of the consumer market, while the other manufacturer's products only occupy a small part of the consumer market, and the manufacturer with a large consumer market has more voice, which will be accepted by consumers even if the price is high. Therefore, for consumers, they prefer manufacturers to balance market prices through full cooperation to maximize their utility. Figure 5 illustrates the above results well.

6. Results and Comments

This paper constructs a supply chain system consisting of one common supplier and two manufacturers and investigates the manufacturer's selection strategies for three different scenarios of full cooperation, partial cooperation, and noncooperation in the competition setting. Simultaneously, the common supplier launches the innovation and obtains the decision-making of each member of the supply chain when the manufacturer selects different scenarios. By comparing the above models, we can find out the following results.

When manufacturers have a large demand in the basic market, to encourage suppliers to improve their innovation level, manufacturers should choose not to cooperate to strive for higher profits, so that suppliers and manufacturers can obtain the maximum benefits, respectively. From the perspective of consumer utility, for the supply chain, if the consumer utility is small, that is, the supply chain will get more profits from the market. Therefore, when the overall demand of products in the basic market is small, the manufacturer should choose full cooperation, and when the overall demand of the basic market is large, the manufacturer should choose noncooperation, to obtain more profits from consumers. For manufacturers, the discussion can be divided into two situations: the first is that the manufacturer's basic market demand is greater. When the competition degree is small, it is more profitable to choose partial cooperation. When competition degree is high, it is more advantageous to choose full cooperation; the second is that the manufacturer's basic market demand is relatively small. At this time, no matter how competition degree changes, choosing noncooperation is the optimal decision. Furthermore, enterprises should also realize that when they are in an advantageous position in the market, choosing not to cooperate is not necessarily beneficial. On the contrary, they should cooperate with other manufacturers in the market to improve their bargaining power and reduce the cost of obtaining products from suppliers to obtain more profits. Cooperation in competition and competitiveness in cooperation are the guarantee for the long-term development of enterprises. For example, in the electric vehicle market, electric vehicle manufacturers

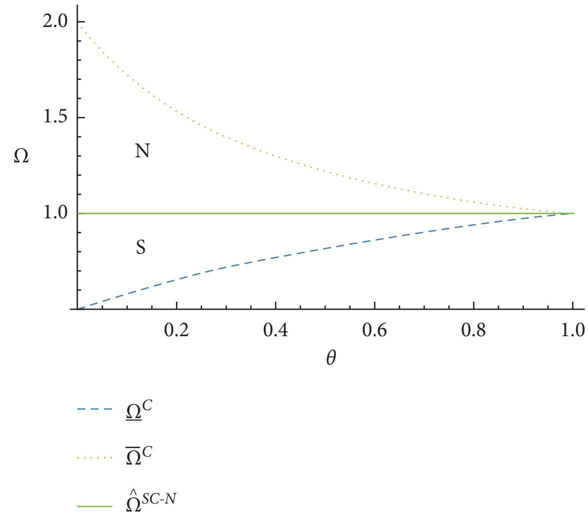

Figure 4: Performance of whole supply chain.

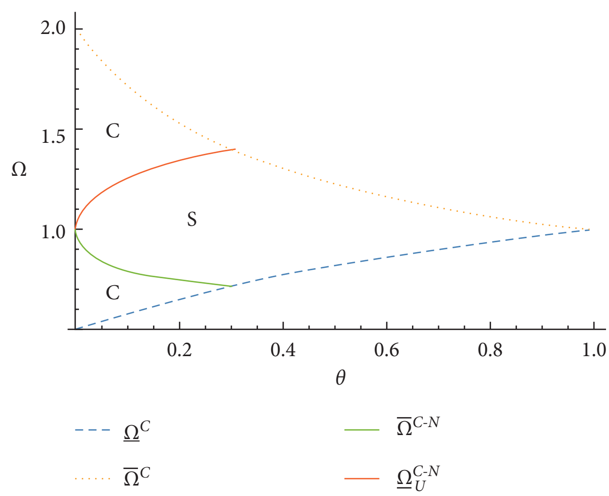

Figure 5: Cooperation preference of consumers.

choose more cooperative behavior to negotiate with suppliers.

At present, the epidemic is still spreading. As a huge supply chain system, any accident in the automobile industry may bring the impact of shutdown or delay in one link of the super long industrial chain, resulting in a chain reaction upstream and downstream of the whole industrial chain. In the supply chain of parts processing and manufacturing, when a supplier closes, other assembly factories that rely on the parts will also suffer heavy losses. Moreover, some parts are not replaceable, and the increase of uncertainty of upstream suppliers leads to the reduction of vehicle assembly output. This kind of "Domino" chain reaction leads to severe risks in the automobile supply chain. In the long run, it is difficult to judge the impact of the epidemic situation and the disruption of the operation rhythm of the industry. Industry insiders believe that the sales side will gradually recover only when the epidemic is controlled, but overall, the sales volume of the car market will be further reduced this year. However, in the face of the epidemic, we can neither ignore the complexity of the global economy nor underestimate its resilience. In extraordinary times, new business models will be promoted or strengthened. The new model, coupled with the huge market volume, means new industrial possibilities. Different from the past, the epidemic situation makes people clearly realize that the only way to ensure human survival is to follow the objective laws of nature and realize the harmonious coexistence between man and nature. Therefore, it is very important to realize the "ecology" of automobile driving and pay more attention to the purification of air in the vehicle and the development of anti-virus, disinfection, and other functions, so as to better protect the safety and health of drivers and passengers, which has become a new direction of automobile technology R&D and innovation in the future.

From the perspective of manufacturers' own market demand, this paper analyzes the influence of different interactions between manufacturers on the decision-making of the supply chain and its members, and the conclusions drawn are inspiring for electric vehicle manufacturers. But this article only considers the scenario when downstream manufacturers have the same technology and does not consider other scenarios, such as the competition situation or when downstream manufacturers have different technologies. In addition, it has not considered whether the decision-making results of supply chain members will change when downstream manufacturers provide cost sharing to the supplier. This scenario can be used as a follow-up research direction.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

College Students' Choice Behavior of Electric Two-Wheeled Vehicle

Rong-Chang Jou, C. W. Lin, and P. L. Wang

Department of Civil Engineering, National Chi Nan University, Nantou 54561, Taiwan

Correspondence should be addressed to Rong-Chang Jou; rcjou@ncnu.edu.tw

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Many countries have made great efforts to boost the use of electric vehicles in recent years; for example, advanced countries including Norway and the Netherlands in Europe and the United States have enhanced people's willingness to use electric vehicles by means of appropriate subsidies and suppression of private vehicles. In Asia, Taiwan has been promoting the policy of replacing traditional fuel two-wheeled vehicles (FTWVs) with electric two-wheeled vehicles (ETWVs) and strengthening the policy by means of replacing a large number of old FTWVs and subsidizing the purchase of ETWVs. This study took college students as the subjects, as they were the first potential group to buy ETWVs, and their concept of environmental sustainability can be shaped for cultivating vehicle use habits. This study applies a questionnaire to probe into the ETWV usage preferences of college students and explores the significant factors affecting college students' purchase of ETWVs. This study uses a mixed logit (MXL) model for estimation. The results of model estimation show that those who are younger, have higher income, have good experience in using ETWVs, and are in user-friendly external traffic environments, are more inclined to choose ETWVs. In the future, government units can formulate policies to promote ETWVs according to the characteristics of different relevant factors.

1. Introduction

Due to the use of biofuels, electrification, and efficient techniques, global transport emissions increased by less than 0.5% in 2019, compared with 1.9% annually since 2000. However, transportation sector still accounts for 24% of CO_2 emissions from fuel combustion. Transport modes including cars, trucks, buses, and two- and three-wheelers are responsible for nearly 75% of transport CO_2 emissions. The result highlights the need for international policies that concentrate on these hard-to-abate subsectors [1]. Electric modes, including electric vehicles (EVs) and ETWVs, have become a policy adopted by governments in response to changes in energy structure and demand. In recent years, while vigorously promoting relevant policies, such as tax credits, parking incentives, purchase subsidies, and other direct measures to benefit consumers in policy development for EVs in the United States, manufacturers have adjusted to the relevant laws and regulations to improve consumer willingness to enter the market, such as economic incentives and relevant building regulations applicable to EVs.

In addition, the Norwegian government, which has high EV use, not only subsidizes the abovementioned relevant policies but also restricts and adjusts the taxes and regulations of fuel vehicles more strictly and strengthens the construction of hardware facilities in a government-led manner to reduce the total cost of ownership (TCO) of users for EVs and ETWVs. For example, from 2015 to 2017, the Norwegian government adopted the method of building charging stations every 50 km along important road systems to expand the power density of the whole road system, and at least two charging piles are constructed in each charging station to completely meet the demand for long-distance charging of EVs. It also announced that it is scheduled to completely ban the sale of gasoline vehicles before 2025.

According to the statistical results of the Department of Air Quality Protection and Noise Control, Environmental Protection Administration (Taiwan) TEDS10.1

(Environmental Protection Administration, 2020), the impact of domestic mobile pollution sources on air quality accounts for about one-third, while the emission of PM2.5 from various pollution sources accounts for 26% of transport vehicles, which shows that, in order to fight against air pollution and climate change in Taiwan, diesel vehicles and automobiles must undergo low-carbon transformation. In addition, according to the survey report of the Department of Statistics, Ministry of Transportation and Communications [2], FTWVs have become the largest transportation mode used by Taiwanese when going out (accounting for 46.6%), and FTWVs produce harmful pollutants every year, which account for 10% of the total national emissions, making FTWVs the main source of air pollution in urban areas. Under the strategy of energy saving and carbon reduction, ETWVs can keep the maneuverability and convenience of the original FTWVs and become the main means of transportation to replace the FTWVs.

There are three sources of government ETWV purchase subsidy in Taiwan (Industrial Development Bureau. Electric Vehicle Industry: https://www.lev.org.tw/subsidy/result.aspx) to replace old vehicles or new purchase: (i) Industrial Development Bureau, (ii) Environmental Protection Administration, and (iii) local county and city governments (see Table 1 for classification). According to the statistics of the Industrial Development Bureau, the number of ETWV subsidies applied for in Taiwan increased from single digits in 2009 to more than 90,000 vehicles in 2020, and the application rate climbed from 0.05% yearly to 1.44% in 2019, indicating that the vehicle purchase subsidy strategy has achieved certain results. Therefore, in order to understand the influence of subsidy measures on college students' choice of ETWVs, this study explored college students' choice behavior of FTWVs and ETWVs under various subsidy measures through the scenario design of a SP questionnaire.

Referring to the abovementioned survey report [2], the analysis results show that the most important factor affecting users' purchase or replacement of ETWVs is the "reasonable price of ETWVs," indicating that the price of ETWV does affect users' purchase intention; if we compare the differences in the repurchase characteristics of the above group, 25.7% of the group members will buy ETWVs a second time; 78.8% of the original ETWV users still buy ETWVs for the second time. This shows that users of ETWVs have a high degree of goodwill and loyalty, and if the usage environment for ETWVs can be further improved, ETWV users will be more willing to buy ETWVs.

There are 1.2 million college students in 2020, which accounts for 5% of Taiwan population [3]. Considering that college students are potential ETWV buyers, this study intended to understand the important factors of college students' choice of ETWVs by exploring the behavior of this group, and the results can be applied to developing effective marketing strategies for ETWVs. Moreover, this study added the types of subsidy measures available in the scheme development situation in order to explore the influence of subsidy measures on college students' choice of ETWVs.

At present, the promotion of ETWVs in Taiwan is mainly dominated by the governmental purchase subsidies, manufacturers' incentives and subsidies, and parking concessions that are granted to consumers; however, there is still a lack of overall consideration and planning for the characteristics, charging requirements, and friendly environment that ETWV users pay attention to. This study is aimed to explore the important factors affecting the purchase of ETWVs (alternatives include traditional fuel and electric two-wheeled vehicles) from the perspective of college students. Among them, it is worth emphasizing that this study took college students as the research subjects, as college students are one of the main potential groups that buy ETWVs as their first vehicle, which means that the cognition and attitude of environmental sustainability have a far-reaching and long-term impact on this group. If they can cultivate their habits of using ETWVs, their contribution to the overall environmental reduction of carbon should be quite significant. It is also worth mentioning that the variables used in this study include a number of subsidy measures (such as purchase subsidy, exemption from specific taxes, and parking fee reduction). Therefore, the impact of subsidy measures on college students' choice behavior of ETWV types can be explored.

2. Literature Review

In order to understand the preferences and characteristics of ETWV users, this study conducted a literature review of ETWVs, which was used as a reference for the design of the follow-up questionnaire. As ETWVs become one of the alternatives to traditional fuel vehicles, their growth rate is quickly increasing. Zhu et al. [4] explored the willingness to buy (WTB) and willingness to pay (WTP) of consumers purchasing ETWVs and adopted the contingent valuation method (CVM). The results showed that respondents pay more attention to the actual costs of ETWV, such as selling price, charging rate, warranty fees, and tax incentives, and achieving the highest speed. However, the education level and the number of family members of the respondents will affect the WTB and WTA of ETWV, and it was estimated that the WTA amount of ETWV is MOP 1315.54 (1 MOP = U$0.13).

Bakker [5] found that the ETWV has a crucial influence on urban transportation planning; however, traditional traffic planning often ignores the ETWV because of its current unpopularity. This study collected the development policies of China, Vietnam, the Netherlands, and other countries for discussion, and the results show that if appropriate measures can effectively improve the utilization rate of ETWVs, such as implementing low emission areas, phasing out traditional motorcycles and improving the traffic-related legal framework, the main planning principle of urban planning will be to increase the attractiveness and safety of ETWVs.

Guerra [6] studied ETWVs as an alternative to traditional fuel vehicles. In order to understand the Solo region of Indonesia, he designed five attributes of ETWVs and traditional FTWVs through a survey questionnaire. According to the price, speed, endurance mileage, and charging time, he invited respondents to check their

Table 1: Amount of subsidy for purchasing ETWVs in Taiwan.

Subsidy unit	Subsidy item	Amount of subsidy	
		Lightweight ETWV	Heavy duty ETWV
Industrial Development Bureau	New purchase	US $252.6	US $252.6
Taiwan Environmental Administration	Replace the old with the new	US $108.3	US $36.1
Local county and city governments	New purchase	US $144.4~324.8	US $36.1~180.4
	Replace the old with the new	US $72.2~324.8	US $72.2

preferred type of transport and applied the mixed logit model for estimation. The results showed that, while it was feasible to implement the ETWV market in the Solo region, the price and performance of ETWVs must be able to compete with traditional FTWVs to gain a market share. Regarding the speed, endurance mileage, charging time, and price, respondents were willing to pay 7–13% more fees to buy ETWVs that feature 10 km more endurance range than the original design, a faster speed by 10 km/hr, and a charging time shortened by one hour. At the same time, the survey results also pointed out that charging time is actually the most important influencing factor, which indicates that improving charging technology and strengthening charging facilities can effectively improve willingness to use.

Thuy and Hong [7] studied and investigated the willingness and attitude of high school students in Ha Noi, Vietnam, to use ETWVs. In order to determine the reasons and preferences that affect students' willingness to use ETWVs, this study used the Theory of Planned Behavior (TPB), and the results showed that the attitude or preference factors of high school students' tendency to use ETWVs included perceived economic benefits, convenience of use, friendly environment feeling, and fashionable appearance design. However, high school students' willingness or purpose to use ETWV is influenced by three factors: individual subjective preference or benchmark, attitude preference to use ETWV, and attractiveness of ETWVs to high school students.

Ferrara et al. [8] explored the usage preference of FTWVs and ETWVs in India and designed five schemes for face-to-face interviews to investigate transportation preferences. The results showed that for individual users, the price and performance of ETWVs are the most subjective direct influencing factors, and when the price and performance of ETWVs reach a certain degree (such as improved battery charging technology), they will have enough attraction for individual users. Other environmental factors that influence the choice of individual users to use ETWVs include the integrity or improvement of the charging infrastructure.

Lee et al. [9] probed into the promotion of E-scooter sharing (ESS) and compared two types of users: one group tended to use the ESS service for commuting, and the other group used ESS service in the first mile and the last mile. The results showed that the socioeconomic characteristics of individuals tend to be younger, have higher income, prefer green energy, are less satisfied with the quality of current public transport services, and they tend to use ESS service frequently.

Eccarius and Lu [10] compared the difference between traditional FTWVs and ETWVs. According to the research results, although fuel driven two-wheeled vehicles have a large impact on air pollution, and ETWVs can meet the needs of most users, the sustainability of ETWVs is not comparable to that of FTWVs. Although the popularization and application of ETWVs are still not as large as that of traditional ETWVs at present, it is a great advantage for the sustainable development of the future environment; thus, it was suggested that ETWVs should be encouraged at the initial stage, and then, the usage restrictions of FTWVs should be gradually adjusted.

Javid et al. [11] investigated the travelers' adoption behavior towards EVs using the theoretical background of the norm activation model (NAM) theory. The collected data were analyzed using factor analysis and structural equation modeling methods. The results showed that car ownership of travelers has a positive correlation with the ownership and usage of EVs. Several approaches were suggested to promote the ownership and usage of EVs. Miralinaghi et al. [12] proposed a framework to address the relationship between consumers' vehicle-purchasing propensities and their route choices, locations of EV-charging, and ICEV-refueling stations. The study can guide the metropolitan transport agencies to establish specific locations and capacities for EV stations. Miralinaghi and Peeta [13] designed a robust multiperiod tradable credit scheme (TCS) to incentivize travelers to shift from internal combustion engine vehicles to zero-emissions vehicles over a long-term planning horizon to reduce vehicular emissions. The robust design can accommodate the uncertainty in forecasting travel demand over years. The proposed TCS design reduced vehicular emission rates under different travel demand scenarios compared to that does not consider demand uncertainty.

3. Methods

The discrete choice model, mixed logit (MXL), that can take preference heterogeneity of individuals into account has been recognized as the most popular econometric method [14]. MXL model also can accommodate with the correlation amongst choice sets drawn from the same respondent. The utility function of the ith alternative for the nth individual can be defined as

$$U_{in} = V_{in} + \varepsilon_{in} = \beta_n' x_{in} + \varepsilon_{in}, \tag{1}$$

where V_{in} is the deterministic utility, ε_{in} is the stochastic component, and β_n is the vector of estimated parameters of the explanatory variable x_n. β_n is assumed to be randomly varied over individuals, and the probability density function

$f(\beta) = (\beta_n \in \beta)$ is represented by parameter θ as the mean and covariance. According to Jou and Yeh [15], the unconditional choice probability of individual n choosing alternative i is given in the following equation:

$$P_{in} = \int L_{in}(\beta_n) f(\beta) \mathrm{d}\beta = \int \left(\frac{e^{\beta x_{in}}}{\sum_{J=1}^{J} \beta x_{jn}} \right) f(\beta) \mathrm{d}\beta, \quad (2)$$

where $L_{in}(\beta_n)$ is the probability of a multinomial logit (MNL) model and P_{in} is the weight of the MNL probability. The heterogeneity of individuals can be captured through fixed socioeconomic characteristics by decomposing β_n into b_k and $\varphi * z$. The details are shown in

$$U_{in} = \beta_n' x_{in} + \varepsilon_{in} = (b_k + \varphi * z)' x_{in} + \varepsilon_{in}, \quad (3)$$

where b_k are random parameters and z represent the attributes of individual n, and φ is the parameter vector of attributes z. If b_k are the parameters of the attributes of the alternatives, Jou et al. [16] indicated that $\varphi * z$ interacts among alternatives and individuals and includes market segmentation effects, such as socioeconomic characteristics of individuals or observed heterogeneity.

To understand the impact of a percentage change in an attribute on the change in the probability of choosing a specific TWV's scheme, we apply the direct and cross elasticities specified in Jou and Yeh [15], expressed as

$$e_{x_{jnk}}^{in} = -\int \beta_k L_{jn}(\beta) \left[\frac{L_{in}(\beta)}{P_{in}} \right] f(\beta) \mathrm{d}\beta, \quad (4)$$

where β_k is the kth element of β. The percentage change in probability depends on the correlation between $L_{in}(\beta)$ and $L_{jn}(\beta)$ over different values of β.

4. Survey Design and Data Analysis

4.1. Survey Design. In order to understand the preference of college students who buy ETWVs for the first time in Taiwan, the questionnaire design was divided into four parts. The first part is a survey of college students' main trip activities and behaviors, the second part is a survey of college students' ETWV use characteristics, the third part is a survey of socioeconomic data, and the fourth part is a hypothetical scenario, all of which are described as follows:

(1) Part I: main trip activity behavior of college students.

The main trip activity behavior survey of college students includes the following: respondents' trip purpose, travel time, origins and destinations, the number of times of general school use, and the transfer/use of transit stations. Please refer to Section 4.2.2 for more details.

(2) Part II: ETWV use characteristics.

This part is aimed at the types of two-wheeled vehicles held (used) by college students, whether they are new vehicles, the use time (year), the mileage (kilometers), and the records of related variable costs (including fuel costs, maintenance costs, and parking costs). The data in this part can facilitate follow-up studies of college students' choice of variables for the purchase of ETWVs.

(3) Part III: socioeconomic characteristics.

The survey of individual socioeconomic characteristics includes the following: (1) gender: male or female; (2) age: from 18 to 23 years old or others (open answers), with a total of 7 sections; (3) residential area: including 29 districts in Taichung city; (4) average monthly income of individuals (including petty cash, part-time jobs, and allowances); (5) average monthly income of household: from below US \$720 to above US \$5038, with every US \$720 being an interval; (6) family members: 1 to 6 or more; (7) types of vehicles at home: check the number of motorcycles and cars, respectively; (8) preference for limiting the maximum service life of ETWVs; (9) whether there is a ETWV in the household; (10) whether the individual has ever used a ETWV.

(4) Part IV: hypothetical scenarios.

The design of the attributes and attribute levels is critical for a choice experiment. We specified five two-wheeled vehicle types with the following attributes provided: maximum capacity, license plate, horsepower, top speed, driving range, recharge time, list price, maintenance cost, fuel cost/recharge cost/battery replacement/rental prices, battery warranty, purchase subsidy, and tax breaks. These attributes were identified as crucial factors influencing the adoption of ETWVs by college students. According to Taiwan's current policy, the incentive policy attributes include purchase subsidy, reduced parking fees, and tax breaks. The incentive's current values were used as a reference point to set attribute levels of the five options and were ensured the rationality of our experimental approach.

Each incentive attribute was designed to three levels, +25%, +50%, and +75%, with respect to its reference point. The base purchase subsidy of ETWV-I and ETWV-II is US \$ 517.00 and US \$ 585.00, respectively. The base reduced parking fee is fixed at US\$ 0.67. The base tax break is US\$ 15. The base tax break is US\$ 46.67. To promote the usage of ETWVs, the practice policy of the parking and tax breaks fee in Taiwan is now free. Therefore, the scenario of ETWV-I and ETWV-II is set at zero.

According to the presented scenarios, the interviewees were asked to answer the types of vehicles they would like to buy in the future. To understand the important considerations for college students to buy ETWVs, the attributes adopted in the experimental design of this study are shown in Table 2. In the selection of the experimental design situations, the orthogonal method was used to reduce the combination of scenarios. Each attribute had two or three levels of values in the nine variable attributes (other attributes are fixed), resulting in $(2^1 \times 3^8)$ scenarios. The number of scenarios was further reduced to 18 groups of scenarios. In order to avoid respondents filling in too many scenarios at

Table 2: Attributes' values and levels for five different vehicle types.

	SC-I (100 cc)	SC-II (125 cc)	MT (150 cc)	ETWV-I	ETWV-II
Vehicle types					
Maximum capacity (people)	2	2	2	2	2
License plate	Written in black on a white background AAA-001	Written in black on a white background AAA-001	Written in black on a white background AAA-001	Written in white on a green background AAA-001	Written in black on a white background AAA-001
Horsepower (hp)	7~8	5.2~8.8	8.5~18.4	1.35~5	5~8.58
Top speed (km/h)	90~100	105~110	120	45	90
Driving range (km)	100	140	150	100	110
Recharge time (h)	—	—	—	4~6	Replacement
List price (US $)	1600~2600	1630~2800	2470~5260	2400~2730	2460~4300
Maintenance cost (US $/year)	66.67	83.33	100	33.33	36.67
Fuel cost (F), recharge cost (R), battery replacement/ rental prices (B; US $/year)	Short trip*: 83.3 (F) Long trip*: 166.7 (F)	Short trip: 93.3 (F) Long trip: 183.3 (F)	Short trip: 100 (F) Long trip: 193.3 (F)	Short trip: 5.3 (R) + 216.7 (B*) Long trip: 11.7 (R) + 166.7 (B*)	Short trip: 200 (B**) Long trip: 240 (B**)
Battery warranty	Unlimited, NA	Unlimited, NA	Unlimited, NA	30,000 km/3 yr 60,000 km/5 yr 90,000 km/8 yr	30,000 km/3 yr 60,000 km/5 yr 90,000 km/8 yr
Purchase subsidy (US $)	0	0	0	+25% base +50% base +75% base	+25% base +50% base +75% base
Parking fees (US $/h)	+25% base +50% base +75% base	+25% base +50% base +75% base	+25% base +50% base +75% base	0	0
Tax breaks (US$/year)	+25% base +50% base +75% base	+25% base +50% base +75% base	+25% base +50% base +75% base	0	0

the same time, each interviewee filled in two groups of scenarios in the questionnaire. Moreover, this study classified five types of two-wheeled vehicles, SC-I, SC-II, MT, ETWV-I, and ETWV-II, in order for the respondent to choose one among five alternatives. SC-I, SC-II, and MT are FTWVs; ETWV-I and ETWV-II are ETWVs.

This study mainly discussed the behavior of college students choosing two-wheeled vehicles in different situations. The subjects were mainly college students in central Taiwan (including Tunghai University, Feng Chia University, Chung Shan Medical University, China Medical University, Asia University, Chaoyang University of Technology, National Taichung University of Science and Technology, National Chung Hsing University, and Hungkuang University). They engaged in one-to-one interviews, and a total of 902 valid samples were collected.

4.2. Sample Representativeness and Data Analyses

4.2.1. Sample Representativeness Analysis. This study conducted sample representativeness analysis according to the data investigated by the Department of Statistics, Ministry of Transportation and Communications in the Survey Report on Vehicle Usage [17], and college students aged 18–45 and with junior college to graduate school education were screened out to verify the sample average. The common items between Survey Report and our study include "weekly fuel consumption amount," "annual maintenance amount," and "monthly parking cost." Therefore, sample representativeness tests were performed in terms of the three items.

(1) Weekly fuel cost:

The average weekly fuel consumption of the sample in this study was about US$3.65/week. Based on the survey results of the Survey Report on Vehicle Usage (2018), the average was US$ 3.66/week. After further verifying the average of this study and survey report, it was found that the null hypothesis is accepted in the significant level of 5%, which shows that there was no difference between the samples of this study and the survey report in this project.

(2) Annual maintenance amount:

The average number of samples in this study was US $68.25/year, and the average number in this survey report was US $70.10/year. Further average testing showed that the null hypothesis is accepted in 5% of the significant level, which shows that there was no difference in the use characteristics between the samples in this study and the same population reported in the survey.

(3) Monthly parking cost:

In the item of monthly parking cost amount, the average number of the sample in this study was US \$2.54/month, and the average number of the survey report was US \$2.58/year. Further verification of the average number of this study sample and the aforementioned vehicle use survey report showed that the result is in the significant level of 5%, which shows that there is no significant difference between the sample in this study and the survey report.

Analysis of the usage characteristics of this study and the Survey Report on Vehicle Usage (2018) showed no significant difference between the survey results of this study and the survey report under the above three vehicle usage characteristics, which shows that the samples of this study are representative (as shown in Table 3).

4.2.2. Data Analysis

(1) Analysis of the Main Trip Activities of Using Vehicles. Analysis of the main activities of vehicle use shows that most college students have two main activities, commuting, which accounts for about 66%, followed by eating, working, or leisure (accounting for about 30%); regarding the purpose of secondary activities, eating and working account for about 63%. In addition, further analysis of college students' vehicle use shows that most vehicles are used for more than 5 minutes, accounting for about 80%; the driving distance of each trip is concentrated in 1~less than 3 km (accounting for about 32%), followed by driving distance which is less than 10 km (accounting for about 84%), and the driving time of each trip is less than 30 minutes (accounting for about 93%). Motorcycles are mostly used for short-distance trips; the average driving speed is between 40 and 70 kph (accounting for 80%), which shows that driving speed is not slow, which may be related to the characteristics of college students' riding habits.

According to the results of exploring the main activities of college students, the number of vehicle use days is mostly more than 5 days (about 72%). Among these results, 7 days account for 45%, which is most noteworthy, as it shows that the short-distance travel service of urban mass transportation for college students may not meet their needs at present; for example, the restrictions on operating hours and boarding places (inconvenient to take public transportation accounts for 19%), low accessibility (high vehicle mobility accounts for 57%, and using vehicles can shorten travel time accounts for 20%), or high boarding costs (low cost of using vehicles accounts for 1.4%). Therefore, more flexible operating hours and higher density of boarding locations would promote a higher usage of public transportation.

This study further explored the transport modes of college students, not including two-wheeled vehicles. Under the purpose of a single trip, 80% no longer transfer or use other means of transportation, among which the main reasons are short distance (no transfer demand), short trip length, uncertain transfer time, and extra waiting time, which lead to no use of other means of transportation (about 19%), and the inconvenience of vehicle parking when transferring is another main reason (about 15%). These results show that college students give priority to convenience for short-distance travel.

(2) Analysis of the Use Characteristics of Two-Wheeled Vehicles. This part analyzed the related characteristics of vehicles used by college students and found that most of the vehicle types used are 125cc, accounting for about 63%; more than 98% of the engines used are four-stroke engines; the purchase amount of vehicles used is between US \$1799 and US \$2879, accounting for about 56%. Most college students spend about US \$2.5–4.6 per week on fuel, accounting for about 53%. Other variable costs, such as monthly parking fees and annual maintenance costs, are concentrated in less than US\$1.8 (about 57%) and US\$53.9 (about 60%), respectively. The aforementioned analysis results also show that, in addition to the possible burden of the purchase amount, the burden of other variable costs can be ignored, as they account for less than 5% of the average monthly income of individuals. Moreover, as two-wheeled vehicles are more convenient than other means of transportation, college students rely on two-wheeled vehicles as their main means of transportation. If the exploration of environmental pollution sources is the starting point, further exploring the important influencing factors of college students' choice of ETWVs will be key to reduce environmental pollution sources.

However, analysis of college students' two-wheeled vehicle ownership and use status showed that more than 73% of college students had just purchased their vehicles, and most were purchased within the last 2 years (about 57%). The usage (accumulated) mileage of newly purchased vehicles was mostly less than 15,000 km, which shows that most users are short-distance users, which is consistent with the aforementioned statistical analysis. On the other hand, if it is a second-hand vehicle, the service life is averaged within 10 years (about 93%).

(3) Analysis of Personal Data. Analysis results of the basic personal data collected from the survey in this study are shown in Table 4. Among them, the proportions of males and females are 45% and 55%, respectively, and the age distribution is mostly 19~21 years old (about 22%, 26%, and 19%, respectively, for a total of about 67%), which mainly includes sophomores to the senior year of university. About 72% of college students earn less than US\$360 a month. About 84% of college students have two-wheeled vehicles that are 5–20 years, which highlights that the expected holding time of vehicles after purchase is quite long, and it is necessary to have greater incentives to promote and motivate users to purchase their ETWVs in the future. In addition, the cross analysis of ETWV holding time and riding experience was further analyzed, and it was found that about

Table 3: Results of the samples' representative tests.

Item	Average		Z-value	Result
	This study	Survey Report on Vehicle Usage (2018)		
Weekly fuel consumption amount	US $3.65	US $3.66	$Z = 0.09$	Accept the null hypothesis H_0
Annual maintenance amount	US $68.25	US $70.1	$Z = 1.12$	
Monthly parking cost	US $2.54	US $2.58	$Z = 0.33$	

Table 4: Basic data analysis.

Title	Question item	Sample (percentage)	Title	Question item	Sample (percentage)
Gender	Male	405 (44.9)	Monthly income of households	Below US $720	43 (4.8)
	Female	497 (55.1)		US $720–1, 439	96 (10.6)
Age	18	72 (8)		US$1439–2159	189 (21)
	19	194 (21.5)		US$2159–2879	156 (17.3)
	20	232 (25.7)		US$2879–3598	143 (15.9)
	21	175 (19.4)		US$3598–4318	99 (11)
	22	123 (13.6)		US$4318–5038	64 (7.1)
	23	52 (5.8)		Above US$5038	112 (12.4)
	Above 24	54 (6)	Number of family members (including oneself)	1	2 (0.2)
Personal monthly income	Below US$0.018	162 (18)		2	14 (1.6)
	US$0.018–0.036	488 (54.1)		3	95 (10.5)
	US$0.036–0.05	116 (12.9)		4	422 (46.8)
	US$0.05–0.07	93 (10.3)		5	246 (27.3)
	US$0.07–0.09	12 (1.3)		6 and above	123 (13.6)
	US$0.09–0.11	19 (2.1)	Number of vehicles	1	127 (14.1)
	US$0.11–0.13	5 (0.6)		2	299 (33.1)
	Above US$0.13	7 (0.8)		3	290 (32.2)
Vehicle service life	Less than 5 years	20 (2.2)		4 and above	186 (20.6)
	5–10 years	215 (23.8)	Household car ownership	0	96 (10.6)
	10–15 years	319 (35.4)		1	453 (50.2)
	15–20 years	224 (24.8)		2	275 (30.5)
	20–25 years	82 (9.1)		3	56 (6.2)
	Over 25 years	42 (4.7)		4 and above	22 (2.4)

64% of college students have no ETWV and no relevant riding experience, while about 26% of college students have relevant riding experience, but do not own a ETWV, which shows that college students are willing to try new types of transportation, as shown in Table 5.

5. Model Estimation and Elasticity Analysis

This study divided the vehicle selection schemes in the SP situation into five categories: "Scheme I: SC-I (100 cc)," "Scheme II: SC-II (125 cc)," "Scheme III: MT (150 cc)," "Scheme IV: ETWV-I," and "Scheme V: ETWV-II." This section calibrated the MXL model first, and then the elasticity analysis was carried out on the estimated model.

5.1. Explanatory Variables for the Model. The definition, mean, standard deviation, and maximum and minimum values are explained according to the explanatory variables of each model, and the relevant explanations are detailed in Table 6, where the last column is other studies using similar variables.

5.2. Model Estimation Results. The estimation results of the MXL model are shown in Table 7, in which the significant variables include "age," "gender," "personal income," "variable cost of vehicles," "acceptable price of ETWV," "classification of main reasons for using vehicles," "looking forward to try/reuse ETWV again," and "tendency to choose ETWVs if you want to buy vehicles in the future." The influence of each variable on college students' choice of vehicles is described as follows. On the whole, younger students tend to buy FTWVs with larger cc (SC-II and MT). In addition to buying fuel vehicles with higher cc, the male students also tend to choose ETWV-II. With higher personal income, people are more willing to buy ETWV-II vehicles. When the variable costs of a vehicle (including fuel cost, maintenance cost, and parking cost) are higher, college students are less inclined to buy a specific fuel vehicle (SC-II). In addition, people who use two-wheeled vehicles due to the inconvenience of mass transportation are less inclined to buy ETWV-I; people who use two-wheeled vehicles due to their high mobility and convenience for other activities are also less inclined to buy ETWV-I. When buying two-wheeled vehicles in the future, those who will directly choose

Table 5: ETWV's holding time and riding experience.

Holding or not of ETWV\riding experience	No	Yes	Total
No	576 (63.9)	232 (25.7)	808 (89.6)
Yes	10 (1.1)	84 (9.3)	94 (10.4)
Total	586 (65.0)	316 (35.0)	902 (100)

Table 6: Description of significant variables in the models.

Explanatory variable	Average mean	Standard deviation	Min	Max	Value setting	References
Gender	0.55	0.49	0	1	0: female, 1: male	Lee et al. [9]; Brückmann et al. [18]; Eccarius and Lu [10]
Age of junior college students	20.63	2.08	18	45	18–45 years old, adopt the actual filled-in value for setting	Lee et al. [9]; Brückmann et al. [18]; Eccarius and Lu [10]
Family size	4.46	1.11	1	12	1–12 persons/household, adopt the actual filled-in value for setting	Brückmann et al. [18]
Personal monthly income	845.29	435.04	360.88	2887.04	Adopt the actual filled-in value for setting	Lee et al. [9]; Brückmann et al. [18]; Eccarius and Lu [10]
Variable cost of two-wheeled vehicle	272.9	117.5	61.4	776.6	Variable cost = fuel cost + maintenance cost + parking fee, which is the value after adding the checked values	Eccarius and Lu [10]
Vehicle purchase price	2124.9	866.9	288.7	7939.4	Adopted the median of the checked value for setting	Eccarius and Lu [10]
Vehicle fuel cost per week	101.651	56.183	22	317	Adopted the median of the checked value for setting	Eccarius and Lu [10]
Reason for choosing traditional vehicles_the price of ETWVs is too high	0.351	0.478	0	1	1: reason for choosing traditional FTWVs_the price of ETWVs is too high 0: otherwise	Thuy and Hong [7]
Reason for choosing traditional vehicles_poor endurance of ETWVs	0.386	0.487	0	1	1: reason for choosing traditional FTWVs_poor endurance of ETWVs 0: otherwise	Thuy and Hong [7]
Reason for choosing electric vehicle_there is a car purchase subsidy	0.240	0.427	0	1	1: reason for choosing ETWVs_those who have purchase subsidies; 0: otherwise	Thuy and Hong [7]
Reasons for choosing electric vehicle_the price of electric car is reasonable	0.053	0.225	0	1	1: reason for choosing ETWVs_the price of ETWV is reasonable 0: otherwise	Thuy and Hong [7]
Choose electric vehicle reason_fuel tax/ license tax exemption	0.192	0.394	0	1	1: reason for choosing ETWVs_fuel tax/license tax exempt 0: otherwise	Thuy and Hong [7]

Table 6: Continued.

Explanatory variable	Average mean	Standard deviation	Min	Max	Value setting	References
Reasons for choosing electric vehicle_good operating efficiency (horsepower, speed, driving distance, etc.)	0.079	0.270	0	1	1: reason for choosing ETWVs_those with good operating efficiency (horsepower, extreme speed, driving distance, etc.) 0: otherwise	Thuy and Hong [7]
It is my duty to take practical actions and buy ETWVs to protect the environment and limit greenhouse gas emissions	3.775	1.068	1	5	1: strongly disagree 2: partly disagree; 3: neutral 4: partly agree 5: strongly agree	Thuy and Hong [7]
I look forward to trying/using ETWVs again	3.534	1.007	1	5	1: strongly disagree 2: partly disagree 3: neutral 4: partly agree 5: strongly agree	Huang [7]; Thuy and Hong [7]; Eccarius and Lu [10]
I think at the current price of ETWVs, it has provided good value	3.044	0.940	1	5	1: strongly disagree 2: partly disagree 3: neutral 4: partly agree 5: strongly agree	Thuy and Hong [7]; Eccarius and Lu [10]
The government cash subsidy policy is very attractive for me to buy ETWVs	3.421	1.046	1	5	1: strongly disagree 2: partly disagree 3: neutral 4: partly agree 5: strongly agree	Eccarius and Lu [10]
I think using ETWVs can improve the quality of going out	3.441	0.927	1	5	1: strongly disagree 2: partly disagree 3: neutral 4: partly agree 5: strongly agree	Thuy and Hong [7]; Huang [7]; Eccarius and Lu [10]
The acceptable price of ETWV	1917.2	824.34	0	1082.6	Adopt the actual filled-in value for setting	—
High household income (greater than the sample average US$2835/ month) + male + agreed to spend more money on ETWVs for environmental protection	0.114	0.318	0	1	0: those who do not belong to this group 1: those who belong to this group	—
High household income (greater than the sample average US$2835/ month) + male + agree that electric car is the first choice to buy a car in the future	0.062	0.241	0	1	0: those who do not belong to this group 1: those who belong to this group	—

Table 7: Estimation results of MXL model.

Alternative	Variable	Coefficient	Standard deviation	$\|b/$St.Er.	$\|P[\|Z\|>z]$	PDF function
Random variable	I will choose ETWV if I want to buy a vehicle (in the future) (ETWV-II)	1.91	0.43	4.40	0.00	Normal
Fuel vehicle 100 cc (SC-I)	—	—	—	—	—	—
Fuel vehicle 125 cc (SC-II)	Constant	3.11	0.34	9.11	0.00	Fixed
	Age	−0.19	0.07	−2.92	0.00	Fixed
	Gender	0.61	0.23	2.68	0.01	Fixed
	Vehicle variable cost	−0.89	0.26	−3.43	0.00	Fixed
Fuel vehicle 150 cc (MT)	Constant	0.42	0.40	1.05	0.30	Fixed
	Age	−0.31	0.08	−3.74	0.00	Fixed
	Gender	2.87	0.32	8.92	0.00	Fixed

Table 7: Continued.

Alternative	Variable	Coefficient	Standard deviation	|b/St.Er.|	|P[|Z|>z]|	PDF function
Regular lightweight electric vehicle (ETWV-I)	Constant	−4.43	0.67	−6.60	0.00	Fixed
	Use vehicle only_inconvenient to take public transportation	−1.05	0.43	−2.45	0.01	Fixed
	Main reason, high mobility and convenience for other activities	−0.96	0.31	−3.09	0.00	Fixed
	I will choose ETWV if I want to buy a vehicle (in the future)	1.63	0.17	9.63	0.00	Fixed
Heavy duty electric vehicle (ETWV-II)	Constant	−10.24	3.19	−3.21	0.00	Fixed
	Gender	0.87	0.40	2.20	0.03	Fixed
	Personal income	0.31	0.17	1.84	0.07	Fixed
	Acceptable price of ETWV	0.21	0.10	1.99	0.05	Fixed
	I look forward to trying/reusing ETWV	0.50	0.29	1.73	0.08	Fixed
Standard deviation of parameter allocation	I will choose ETWV if I want to buy a vehicle (in the future) (ETWV-II)	0.75	0.34	2.18	0.03	—
	LL (0)	−1231.091				
	LL (β)	−980.531				
	ρ^2	0.204				

Table 8: Elasticity analysis of socioeconomic and vehicle use characteristics.

Variable	Fuel vehicle			ETWV	
	100 cc SC-I	125 cc SC-II	150 cc MT	Lightweight ETWV-I	Heavy duty ETWV-II
Age (SC-II)	0.313	−0.358	0.313	0.313	0.204
Age (MT)	0.215	0.215	−0.852	0.215	0.140
Gender (SC-II)	−0.135	0.205	−0.135	−0.135	−0.089
Gender (MT)	−0.576	−0.576	1.006	−0.576	−0.383
Gender (ETWV-II)	−0.051	−0.051	−0.051	−0.051	0.269
Personal monthly income (ETWV-II)	−0.083	−0.083	−0.083	−0.083	0.399
Variable cost (SC-II)	0.299	−0.376	0.299	0.299	0.199
Acceptable price of ETWV (ETWV-II)	−0.128	−0.128	−0.128	−0.128	0.579

Table 9: Elasticity analysis of the policy promotion strategy.

Variable	Fuel vehicle			ETWV	
	100 cc SC-I	125 cc SC-II	150 cc MT	Lightweight ETWV-I	Heavy duty ETWV-II
Use only vehicles_people with inconvenience due to public transportation (ETWV-I)	0.019	0.019	0.019	−0.175	0.006
Use only vehicles_high mobility and convenience for other activities (ETWV-I)	0.062	0.062	0.062	−0.485	0.021
If I want to buy a motorcycle now (in the future), I will choose an electric vehicle (ETWV-I)	−0.883	−0.883	−0.883	4.218	−0.284
I look forward to trying/using the electric vehicle again (ETWV-II)	−0.211	−0.211	−0.211	−0.211	0.881
If I want to buy a motorcycle now (in the future), I will choose an electric vehicle (ETWV-II)	−0.834	−0.834	−0.834	−0.834	3.686

ETWVs will tend to choose ETWV-I and ETWV-II. Moreover, the higher the price of ETWV, the more likely college students are to choose ETWV-II. Finally, those expecting to try/reuse ETWVs tend to buy ETWV-II. The main advantage of using MXL model is that random parameters can be tested, and the unobservable heterogeneity of individuals can be further explained by setting random parameters. The coefficient of “if you want to buy vehicles in the future, you tend to choose heavy duty ETWVs” has normal distribution and is statistically significant, which shows that college students’ purchase of heavy duty ETWVs will be influenced by the heterogeneity of college students’ tendency to buy ETWVs in the future.

5.3. Elasticity Analysis. Further elasticity analysis was carried out for socioeconomic, vehicle use characteristics, attitude tendency, and incentive policy, which are all explained, as follows:

(1) Socioeconomic and vehicle use characteristics:

Table 8 shows the percentage of change in the probability of each option when the value of each variable changes by 1% (or 1 unit). The analysis results show that, when the age of college students is higher, they are less inclined to buy SC-II and MT, and the purchase probability of other vehicle types will increase by 0.14%~0.313%. Males tend to buy SC-II, MT, and ETWV-II, while the purchase probability of other vehicle types will decrease by 0.089%~0.576%. If the monthly income of individuals is higher, they will be more inclined to buy ETWV-II, and the purchase probability of other vehicle types will decrease by 0.083%. If the variable costs of vehicles are higher, they are less inclined to buy SC-II, but the purchase probability of other vehicles will increase by 0.199%~0.299%. Finally, people who are willing to pay higher amounts for ETWVs tend to buy ETWV-II, but the purchase probability of other types will decrease by 0.128%.

(2) Analysis of attitude tendency:

Table 9 shows the percentage change in the probability of each option when the value of each variable changes by 1% (or 1 unit). The analysis results show that, if you belong to the group that uses vehicles due to the inconvenience of public transportation, you will be less inclined to buy ETWV-I, and the purchase probability of other vehicle types will increase by 0.006%~0.019%. By the same token, if you belong to the group that uses vehicles due to its high mobility and convenience to engage in other activities, you will be more inclined not to buy ETWV-I, and the purchase probability of other vehicles will increase by 0.021%~0.062%. If members of this group want to buy a vehicle in the future, they will choose the group of ETWVs and be more inclined to buy ETWV-I and ETWV-II vehicles, but the purchase probability of other vehicle types will be reduced by 0.284%~0.883%. In addition, the ETWV-II is more likely to be purchased in the category of "looking forward to try/reuse ETWVs," but the purchase probability of other vehicles will be reduced by 0.211%.

6. Conclusions and Suggestions

At present, the ETWVs available in the current market cannot effectively attract consumers who are buying ETWVs for the first time, which may lead to a sales window due to high selling price, insufficient establishment of related equipment (charging or maintenance), and limited experience/trust in ETWVs. Therefore, in this study, the potential groups (college students) of buying ETWVs in the future were investigated by questionnaire, and their choice preferences were explored, in order to know whether the potential consumers or ethnic groups have different dependence and usage requirements for ETWVs, as compared with fuel-driven vehicles. According to the abovementioned research and analysis, the results are summarized as follows.

6.1. Conclusions

(1) According to the results of MXL estimation, the factors that influence the choice of the fuel vehicle scheme include "age," "gender," and "variable costs of vehicles." The factors that influence the choice of the ETWV vehicle scheme include "gender," "personal income," "acceptable price of ETWV," "If I want to buy a vehicle now (in the future), I will choose an electric vehicle," and "I look forward to trying/using an electric vehicle."

(2) In addition, the coefficient of the random parameter "If I want to buy a vehicle now (in the future), I will choose an electric vehicle (ETWV-II)" in the MXL is normal distributed and significant, which shows that college students hope to have different choices for ETWVs through vehicle purchase schemes in the future.

(3) Moreover, college students who choose the fuel vehicle scheme can be divided into three ethnic groups: male, younger, and those who prefer heavy duty fuel vehicles; for those who choose the ETWV vehicle scheme, there are four groups: male, college students with higher personal disposable income, willing to pay a higher amount for ETWV, and expecting or trying to use it.

(4) The results of elasticity analysis show that the probability of ETWV purchase (including ETWV-I and ETWV-II) will increase under specific groups; for example, groups with socioeconomic or usage characteristics, such as males, those with higher personal income, and those who are willing to pay a higher price for a ETWV, will have a higher probability of a ETWV purchase by 0.199%~0.579%.

(5) According to the results of attitude tendency analysis of elastic analysis, the groups with higher purchase probability of a ETWV (including ETWV-I and ETWV-II) can be subdivided into two categories: those who belong to the category "I expect to try/use ETWVs again" and those who belong to the category "I will choose ETWVs if I want to buy vehicles now (in the future)," both of which have higher purchase probabilities of ETWV by 0.881%~4.2182%.

(6) Practically speaking, the carbon emission of FTWVs is 0.055 kg/km which is twofold of the one of ETWVs which is 0.0265 kg/km [19]. According to the data shown in MOTC [2], the average of total distance traveled by TWs per year is around 3000 km. There are 1.2 million college students in 2020, which accounts for 5% of Taiwan population [3]. If we assume, ideally, at least 80% of the college students use ETWVs, the environment will benefit from the reduction of emissions by at least 82,000 tons of carbon emission per year.

6.2. Suggestions. The following suggestions are summarized according to the above conclusions:

(1) Develop marketing strategies for different age groups:

The younger group of college students have a higher probability of buying ETWV-I and ETWV-II by 0.140%~0.313%, respectively, and this phenomenon shows that age has an impact on the purchase probability of ETWVs. In the future, efforts should be made to promote test drives of ETWVs. When introducing related activities or marketing strategies, it is suggested to subdivide the age groups of college students; for example, high school graduates, freshmen, and sophomores can be introduced to market lightweight ETWVs as short-distance commuting modes around campus, which will enable college freshmen to become familiar with the driving mode first. At the same time, their first vehicle can be purchased at a lower price, which is conducive to the promotion and use of ETWVs.

For junior to graduate students, as they are familiar with the various places around campus (e.g., restaurants and famous shops) and have a wider range of activities, as compared with freshmen and sophomores, heavy duty ETWVs can be marketed for college students of this age group. The endurance, power, and price of heavy duty ETWVs are larger than those of lightweight ETWVs, thus college students can travel locally, commute, and even travel around the island, which will improve the purchase probability of heavy duty ETWVs.

(2) Gender-oriented promotion strategies:

According to the premise of choosing the ETWV scheme, male college students are more willing to buy ETWVs, which shows that some usage characteristics of ETWVs can attract male groups, thus it is suggested that the promotion of ETWVs can be designed to attract the younger male group of college students to improve their purchase intention. For example, Gogoro 2 Rumbler was designed to attract male users by using favorable color matte coating (silver and black) and 12-inch multifunctional tires which can accommodate different terrain. On the other hand, since the preference rate of ETWVs for female users is lower, more actions are applied to promote ETWVs by the industries. For example, the weight of vehicle, the angle of handles, the height of chair, and the space of storage were adjusted according to the figure of female users.

(3) Plan to promote vehicles to different groups:

According to the results of this study, the higher the personal income of college students, the higher the probability of choosing ETWV. This phenomenon shows that the family economic status or personal disposable income should be relatively abundant. Therefore, it is suggested to design and plan different ETWV promotions according to different stages; for example, ETWV equipment, power, and matching monthly fee schemes can be differentiated to meet the use needs of college students at different income levels. Moreover, exclusive monthly fee schemes or vehicle purchase schemes can be designed for college students, meaning students with different statuses can be provided with different purchase preferential schemes to improve their ETWV purchase intention.

(4) Different warranty and rate schemes:

In the factor of variable costs, when the variable costs of a vehicle are higher, the probability of buying ETWV will increase by about 0.199%~0.299%. This phenomenon shows that, when the variable costs of traditional fuel vehicles are too high, the disposable income of college students will decrease, thus reducing the variable costs of ETWVs can attract college students to purchase. Specific practices can be matched with different warranty schemes under the combination of different rate schemes; for example, the basic scheme is designed for basic usage (fixed mileage in a single month), the "no regular return to the factory maintenance scheme", medium usage (such as 300–600 km mileage in a single month) with the "regular back-to-factory maintenance scheme," or high usage (600–1000 km mileage in a single month) with the "regular back-to-factory maintenance and limited warranty scheme." Thus, combinations of different warranties and rate schemes can increase the purchase probability of ETWVs.

(5) Strengthen the use experience and experience feedback of experienced and new users:

Regarding the groups that are willing to pay higher prices for ETWVs, their concepts and perceptions of ETWVs are supportive and positive, thus it is suggested that freshmen can be targeted in follow-up promotion strategies. New ETWV usage experience or "ETWV Experience Meeting of Special Groups" can be held among students who are about to become graduate students (for example, when a manufacturer's new mobile phone is published, invitations will be sent to experienced members or new members to experience the functions of the new mobile phone through invitation, which achieves good use experience and promotes purchase), thus these two groups were selected. Regarding freshmen who are willing to pay a higher amount for ETWVs, the use experience and experience feedback of their first vehicle will often affect the type selection of replacement vehicles in the future, thus, if effective marketing and experience can be carried out for such groups, the willingness to buy ETWVs should be enhanced; regarding college students who are about to become graduate students, meaning the change from university stage to academic research stage, as they are familiar with the surrounding environment and the service life of vehicles is limited, if we can match the strategies mentioned in points 1 to 4 above to promote different combination schemes, we can also effectively improve the willingness to buy ETWVs for students who are willing to pay higher prices.

In addition, for the groups of "I look forward to trying/using ETWVs again," "If I want to buy a vehicle now (in the future), I will choose ETWVs," "I have a good impression of ETWVs," and "I tend to use ETWVs," the development of different promotion strategies can be coordinated with the above-mentioned similar "ETWV Experience Meeting of Special Groups (that is, ETWV club activities organized by manufacturers)," meaning user groups who have used or owned ETWVs in the past can be targeted. While those who have used (or held) ETWVs in the past have good experience in using ETWV, they may not be familiar with the new models, new rate schemes, and accessory combinations, thus such features can be used to promote new models to increase the purchase intention of ETWVs.

(6) Reinforce the gap of public transportation by ETWVs:

For the group of "only use vehicles due to the inconvenience of public transportation," as public transportation is underdeveloped in some areas, this group will tend to use vehicles. However, as underdeveloped public transportation is often located in remote or sparse areas in peripheral business districts, lightweight ETWVs are not preferred to be purchased and used. In this regard, private transport modes that feature mobility, endurance, and a good warranty are favored by college students, such as 100 cc fuel-driven vehicles, heavy duty 150 cc vehicles, or even heavy duty ETWV-II. Therefore, at this stage, public bike sharing (PBS) is often adopted for "the last mile" in Taiwan. In addition to PBS, E-scooter sharing (ESS) services have been deployed for short- and medium-range (3~6 km) connections, but the ETWV models are mainly ETWV-I models. If ETWV-II or above can be introduced in the future to provide a faster driving experience to reach the destination, it should effectively improve the willingness of college students to use or purchase heavy duty ETWVs.

(7) The sample target was the college student who was riding FTWVs at the time of survey conducted.

The questionnaire asked, which alternative they would choose if they were going to replace the old one (FTWV)? Five alternatives including 3 types of FTWVs and 2 types of ETWVs were presented. As such, the ownership of TWVs remains the same, except the emissions are reduced. Meanwhile, promoting programs should keep on for all of the groups. In this way, a synergy of public transit, shared mobility, and EVs will be more effective.

Data Availability

Data can be available upon request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Travelers' Adoption Behavior towards Electric Vehicles in Lahore, Pakistan: An Extension of Norm Activation Model (NAM) Theory

Muhammad Ashraf Javid,[1] **Nazam Ali**,[2] **Muhammad Abdullah**,[3] **Tiziana Campisi**,[4] **and Syed Arif Hussain Shah**[5]

[1] *Department of Civil and Environmental Engineering, University of Nizwa, Birkat al Mouz, Nizwa 616, Oman*
[2] *Department of Civil Engineering, University of Management and Technology, Lahore 54770, Pakistan*
[3] *Department of Civil Engineering, National University of Computer and Emerging Sciences, Lahore 54700, Pakistan*
[4] *Faculty of Engineering and Architecture, University of Enna Kore, Cittadella Universitaria, Enna 94100, Italy*
[5] *Department of City and Regional Planning, University of Engineering and Technology, Lahore, Pakistan*

Correspondence should be addressed to Tiziana Campisi; tiziana.campisi@unikore.it

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This study aims to identify the travelers' adoption behavior towards electric vehicles (EVs) using the theoretical background of the Norm Activation Model (NAM) theory. A questionnaire was designed and conducted in Lahore, Pakistan. A total of 402 usable samples were obtained. The collected data were analyzed using factor analysis and Structural Equation Modeling methods. The factor analysis confirmed the hypothesis of the statements designed according to the NAM theory, that is, awareness of consequences (AC), ascription of responsibility (AR), and personal norm (PN). Other factor analyses resulted in the following reliable factors: social and economic values (SEV), personal preferences (PP), willingness to buy (Buy), and willingness to use (Use) of an EV. The results of SEM revealed that the AC, AR, and SEV are significant predictors of PN, whereas the PN and PP are also positive predictors of travelers' willingness to buy and use. The young travelers (≤30 years), motorcycle users, employees, and trip distance (>10 km) have significant and positive correlations with the PN. The car ownership status of travelers has a positive correlation with the ownership and usage of EVs. Suitable behavioral intervention techniques were derived to promote the ownership and usage of EVs in the context of developing regions.

1. Introduction

In recent decades, environmental pollution has been considered as one of the main causes of global warming, air pollution, and climate change. At the moment, the world is going through some of the most urgent issues such as energy scarcity, emissions of Greenhouse Gases (GHGs), and air pollution [1]. The transport sector is a major contributor of carbon dioxide (CO_2), which emits around 23% of its total emissions [2] and is among the main reasons behind global warming. In this pretext, electric vehicles (EVs) are one of the potential alternatives which can substantially reduce the amount of CO_2 emission, provided that the electricity is produced through renewable energy sources [3]. However, from the economic viewpoint, a major reason which impedes the adoption of electric vehicles as compared with conventional vehicles is their acquisition costs and limited range of driving due to insufficient battery technologies [4, 5]. The inclusion of electric vehicles and the reduction of emissions related to national vehicle fleets were studied by comparing different scenarios using traffic simulation in several countries [6, 7]. According to McKinsey's EV index, which assesses the readiness of nations for the adoption of EVs, Japan, the United States, France, Germany, and China are standing in descending order. The automotive industries are buckling up to lower the operation costs of EVs and reduction of CO_2 emissions [8].

Pakistan is facing some severe environmental challenges including air contamination, water pollution, and deteriorated quality of air due to smog in major cities, which are largely due to unplanned growth and reliance on nonrenewable energy sources [9]. The growth in the industrial and transport sector has been on the rise in recent years because of the increased population. In road transportation, the share of EVs is relatively negligible as compared with conventional vehicles, which are the main causes of CO_2 emissions. It has been estimated that the amount of CO_2 will increase from 858 kg/year to 1650 kg/year by the end of 2030 [10, 11]. Moreover, transport sector is among the three largest sources of CO_2 emissions in Pakistan [11].

The local and central governments are under great stress to alleviate these environmental problems through policy interventions and mitigate the ecological damage on an urgent basis. In this context, the adoption and promotion of electric vehicles are promising efforts to substantially mitigate the emissions of CO_2 especially when electricity is produced through renewable energy sources [12]. In comparison with the conventional vehicles, EVs have many advantages in terms of social, economic, societal, and environmental aspects such as reduction of carbon emissions, improvement of energy security, and promotion of the usage of renewable and clean energy alternatives [13]. Many governments around the world are initiating different incentive programs for the uptake of electric vehicles. The US has implemented the federal tax credit of 7500 dollars, exemption from sales tax, and reduction in the license fee for the adoption of EVs. This initiative was meant to popularize the adoption of EVs and minimize the impacts of higher selling prices [14]. Similarly, the Japanese government has introduced a free charging policy to encourage the usage and adoption of EVs [15]. The Ministry of Science and Technology of Pakistan is keenly interested in the promotion of EVs to mitigate environmental pollution and energy problems in the country. The government of Pakistan is considering incentives and subsidies to encourage people to adopt EVs [12].

Governments around the globe are serious to address environmental concerns through sustainable transport policies including promoting the share of EVs in the market. The understanding of customers' behavior towards the purchase and usage of EVs will provide a clear insight into how these issues can be battled to save environmental degradation [16]. Several studies explored the areas of EV adoption and purchase intentions [4, 13, 17–24]. These studies reported that purchase price and travel ranges are the predictors of EV purchase. It is found that the spread of electric vehicles is closely linked to the spread of recharging areas, which allow a widespread diffusion of these transport systems [25]. In addition, the introduction of electric car-sharing in cities can be an ideal solution for people to test electric cars on the road and to highlight their convenience and advantages over vehicles with combustion engines. It is, therefore, an opportunity to educate people about electric mobility and to get them used to EVs before they buy them [26]. Electric car-sharing is also the most efficient solution for cities as it combines car-sharing with zero-emission technology, with positive effects on both traffic congestion, thanks to the reduction of cars on the road, and the environment, thanks to zero-emission traffic [27, 28]. The integration of demand response transport (DRT) with electric vehicles can provide significant environmental, economic, and social benefits; however, it presents challenging planning issues due to EV charging constraints [29–31].

Given the shortcomings in the literature, especially in a developing country like Pakistan, this study attempts to explore the travelers' EVs purchase and usage intentions through the application of the Norm Activation Model (NAM) theory. This may assist the researchers in identifying the driving factors for the adoption of EVs in developing countries with similar socioeconomic and infrastructural characteristics. Furthermore, it proposes a framework for the encouragement and adoption of green mobility implementation. A comprehensive questionnaire was designed in this study, which was conducted in Lahore city. The factors affecting the travelers' willingness to buy and use an EV were identified using factor analysis and Structural Equation Modeling techniques.

The rest of the paper is organized as follows: in Section 2, relevant literature studies are mentioned, and Section 3 describes the data collection and organization of the questionnaire survey. Section 4 discusses the research results and main findings of this research study. Finally, Section 5 summarizes the main findings and proposes some policy interventions for the promotion of EV adoption in Pakistan.

2. Literature Review

Mainly, researchers have adopted two streams of research to explore the customers' behavior for the adoption of EVs. The first stream includes the role of instrumental attributes of EVs which play a significant role in the adoption of EVs. For example, the purchase price, performance, driving range, and recharging time have a significant impact on the purchasing intentions of the customers [32]. In this strand of research, usually, three sets of factors are considered as predictors for the adoption of EVs: consumer characteristics, technological factors, and contextual factors [33]. Consumer characteristics include the roles of gender, age, income, education levels, and social status as predictors for the adoption of EVs [34, 35]. In the technological factors, battery performance, driving range, and charging time are considered as predictors for the adoption of EVs [36]. The contextual factors involve the use of different policy interventions, fuel prices, and the availability of infrastructure as a guiding tool for the prediction of customers' behaviors [37, 38]. In addition, travelers who drive more especially for longer distances are more likely to prefer EVs [39].

However, the second stream includes the pro-environmental and economic perspectives to determine the purchasing behavior of the customers. Some studies have reported that environmental concerns and environmental attributes have a significant impact on the purchasing and adoption behavior of EVs in the customers [40, 41]. Similarly, a study discussed many advantages and disadvantages of EVs and explored the environmental concerns as a measure for the purchase intentions of the customers [42]. They measure the environmental concern in the sense that "owning an EV will indicate care for the environment." Reference [43] also focused on the intentions of buying EVs and measured the environmental risk of conventional gasoline vehicles as well. Junquera et al. considered the purchase price (economic perspective) and its range for the measurement of customers' intentions to buy EVs but ignored the environmental dimensions [44]. Researchers explored the differentiated approach in the purchasing of high and low EVs and explored the generic perspective about the environment; for example, "it is important to drive a car that harms the environment as little as possible" [45]. Hence, they did not explore the EV-specific environmental performance in their study and no comparison was made between price and range concerning the economic point of view. However, a study explored the environmental concern, which was defined as "the degree to which people are aware of problems regarding the environment and support the effort to solve them or indicate the willingness to contribute personally to the solution" [40]. Again, they followed the generic approach concerning the environmental dimension and did not investigate the economic standing and environmental performance of EVs on customers' purchasing intention. Due to the environmentally friendly nature of EVs, the adoption behavior of customers involves self-interest and altruism. In addition, Perceived Customer Effectiveness (PCE), which is an estimate of the contribution of a customer in solving the problem, also plays an important role in solving proenvironmental behaviors [19, 46]. The customers who believe that they can contribute their part to proenvironmental behavior would utilize their consciousness as a guiding tool for their behaviors. In addition, researchers also focused on optimizing the charging infrastructure to further reduce the emissions and subsequently fulfill the needs of the users [47, 48].

The NAM theory was developed by Schwartz to explain the prosocial and environmentally friendly behavior of the customers [49]. The NAM theory has been used by many researchers to explore the proenvironmental behavior of consumers in different dimensions such as reducing car use [50], recycling [51], and energy-saving behaviors [52]. The NAM contains three primary variables, namely, personal norms (PN), awareness of consequences (AC), and ascription of responsibility (AR). PN represents the moral obligation to perform or refrain from specific actions. It plays a vital role in the NAM and is used to predict altruist (prosocial) behavior. AC represents the awareness about the negative consequences of nonaltruistic behavior and AR represents the feelings of responsibility for the negative consequences arising as a result of nonaltruistic behavior.

Several researchers have used NAM theory and its extensions to model the proenvironmental behavior of travelers to adopt electric vehicles. Researchers employed an extended NAM model to explain the relationship between personal norms and the intentions to adopt electric vehicles [53]. They reported a significant influence of personal norms (PN) on the intentions to adopt EVs, which was moderated by external costs. In addition, AC, AR, and perceived consumer effectiveness were found to have a positive influence on PN. Other existing studies also show that PNs are positively related to prosocial behavior such as intentions to adopt alternative fuel vehicles [54–56]. However, it is believed that many times customers fail to act in a proenvironmental behavior because of the costs involved, that is, monetary costs and behavioral costs [57]. Though customers agree and approve the environmental benefit of EVs, still they are reluctant to act because of the incurred higher costs of purchasing (economic concerns), driving range, and availability of charging infrastructure [18]. A summary of relevant literature concerning the scope of this study is presented in Table 1.

As mentioned above, many of the previous research studies have explored and investigated different dimensions of EVs ranging from price range to economic and environmental concerns regarding the purchase intentions of customers. However, none of the previous studies explored the adoption behavior of customers regarding EVs in the contexts of prosocial and proenvironmental behaviors in Pakistan. In this research study, NAM theory is applied to study the altruistic behavior of customers for the adoption of EVs from prosocial and proenvironmental behaviors in Pakistan. Some of the external factors of socioeconomic characteristics of the customers are introduced in the model to study how they influence and affect the adoption of EVs. Overall, the contribution of this research study in the body of the existing literature is twofold. Firstly, it explores the determinants of purchase and usage intentions of EV customers using NAM theory in a developing country, that is, Pakistan. Secondly, the social, economic, and environmental concerns are added as moderators within the relationship of NAM theory factors and EVs purchase and usage intentions. This proposition might answer researchers who advocated that the incorporation of the knowledge (about the environment, social costs, and EVs) into holistic multivariate modeling can effectively help in predicting the intentions of customers about their purchase and usage intentions [19].

3. Research Methods

3.1. Characteristics of the Study Area. This research study was conducted in Lahore city, which is the second biggest city in Pakistan and the capital of the most populated province of the country. According to an estimation, the population of Lahore city is more than 11 million [70]. In recent years, the city has expanded exponentially because of the increased economic, educational, healthcare, and recreational opportunities in the city. This city is surrounded by the industrial sector, which is a main source of employment in the region, thus attracting many of the inhabitants to settle in the city for better living opportunities. This increased population has created an influx which accelerated the need for traveling in the city. However, the public transport system of the city is not adequate to meet this demand, which has led to a rapid increase in private car ownership in the recent years. This increased private vehicle ownership mostly consists of conventional vehicles with a negligible share of EVs in the city. The emissions from these conventional vehicles have greatly worsened the air quality and the city is facing severe smog issues in the winters and burning heat

Table 1: A summary of relevant literature.

Authors	Country	Summary of important results
Nordlund et al. [58]	Sweden	(i) Hybrid EV/plug-in hybrid EV/EV owners were significantly more receptive to change and less conservative and manifested more self-efficacy and problem awareness, as well as a higher moral obligation, compared to the owners of CVs and alternative fuel vehicles.
Asadi et al. [59]	Malaysia	(ii) Perceived value, attitude, the AR, AC, PN, subjective norm (SN), and perceived consumer effectiveness influenced the EVs purchase intentions.
Dong et al. [60]	China	(iii) EV customers are more apprehensive about cruising power and availability of charging stations. (iv) In addition, perceived behavioral control (PBC), PN, SN, and feelings and emotions influence the intentions of urban households to purchase EVs.
Westin et al. [61]	Sweden	(v) Education and age were found to have positive effects on EVs ownership. (vi) In addition, PN was found to be the most important factor affecting the ownership of EV.
Cui et al. [62]	China	(vii) The results found the environmental concern (EC) to be the most significant driver of the motivation to buy EVs.
Wahl et al. [63]	Germany	(viii) The respondents' anticipated effort, PN, expected performance, and facility conditions significantly affect EVs adoption intentions.
Bockarjovaand Steg, [43]	Netherlands	(ix) Customers were especially more likely to embrace EVs when perceived negative outcomes of CVs were more serious and when EVs were expected to reduce these consequences.
Ng et al. [64]	Hong Kong	(x) Perceived value, responsive efficacy, willingness to pay, and trust in EV had significant and positive effect on the intentions to purchase EVs.
Xu et al. [65]	China	(xi) EV driving experience directly as well as indirectly influences the intentions to adopt EVs.
Shalender and Sharma [66]	India	(xii) Attitude, SN, moral norm, PBC, and EC have a positive relation with the EVs adoption intentions.
Chu et al. [67]	Korea	(xiii) Patient people and people with higher car usage are more probable to be early adopters of EVs.
Higueras-Castillo et al. [68]	Spain	(xvi) Driving range, reliability, and incentives are the most reliable drivers of the intentions to purchase EVs.
Bobeth and Kastner [69]	Germany	(xv) Personal norm appeared to be an important predictor of EVs adoption intentions.

waves in the summer season each year, which is getting intense each passing year. As EVs are potential alternatives for reducing emissions of GHGs and CO_2, there is a great need to explore the purchase intentions of customers towards EVs in the city. This is one of the compelling reasons which motivated the objectives of this study and that is why this study is selected to extract some of the predictors of willingness to buy and willingness to use EVs in the city. It is high time to look for the potentials of EVs in Lahore city keeping in view the deteriorated environmental quality.

3.2. Questionnaire Design. A comprehensive questionnaire was designed to achieve the aforementioned objectives. The respondent's socioeconomic demographics (SEDs) were in the first part of the questionnaire. These SEDs included gender, age, marital status, income, profession, education, car ownership, and travel mode and trip frequency with the same mode, trip cost, and trip distance of the daily one-way trip. The second part of the questionnaire consisted of several statements that were designed based on the variables of the NAM theory and personal preferences and perceived social and economic values in traveling. The variables of AC, AR, and PN were measured using two statements each. The AC variable was measured seeking the travelers' awareness related to the deterioration of the urban environment due to excessive use of gasoline or diesel vehicles and waste of natural resources such as oil or gas. The AR variable measures the travelers' sense of responsibility regarding consumption of natural resources and environmental pollution due to the use of gasoline or diesel vehicles. The PN variable assesses the travelers' moral obligations for the betterment of the urban environment and society and to preserve natural resources. Some statements were constructed to know the travelers' perceived social and economic values in traveling and personal preferences. It was assumed that social and economic values and personal preferences in traveling may have a significant influence on people's PN, willingness to buy, and using an EV. Three statements were designed to get responses on travelers' willingness to use EVs. The willingness to use an EV was asked considering the scenario of preservation of natural resources, reduction of air pollution, and availability of cheap electricity. Four statements were designed for willingness to buy an EV. The presented scenarios for willingness to buy included cheaper than gasoline/diesel cars, maintenance and battery costs less than gasoline/diesel cars, proper information on mileage, and long life of batteries. All the statements of the second part were evaluated using a five-point Likert scale for level of agreement, that is, strongly disagree (1), disagree (2), neutral (3), agree (4), and strongly agree (5). This scale was chosen considering the reliability of the data and the easiness and understanding of the respondents in reporting the responses to each statement.

3.3. Surveying and Sampling Methods. This survey was conducted with the target population in Lahore city. The target respondents included the current car users and non-car-users who have the potential to own an electric vehicle in the future. The users of various modes belonging to different economic groups were included in the target sample. A convenience-based random sampling strategy was adopted in this survey. The target respondents were selected randomly at each selected location in the study area. The selected locations included some commercial activity centers, government and private educational institutions, and official buildings, where it was easy to get the required respondents. The required sample size was decided considering the requirements of Structural Equation Modeling (SEM). A sample size of 200 is required to minimize the bias in the results [71, 72]. Suggestions also included a ratio of 10 observations or samples per indicator [73], and the sample size should be at least 10 times the number of free parameters in the model [74, 75]. In this study, a sample size of around 400 was decided based on the mentioned recommendations. This survey was conducted with the help of university students. The students were trained and instructed regarding the contents of the questionnaire and survey techniques. All efforts were exerted to ensure the reliability of the collected data for the extraction of exact responses. A total of 402 useable samples were collected within three weeks.

3.4. Data Modeling Specifications. The collected data were analyzed using factor analysis and SEM methods. The SEM is a multivariate statistical analysis tool used to construct the correlations between the explanatory and objective variables. Initially, factor analysis was performed to confirm the correlations of observed variables with their corresponding factors or latent variables according to the NAM theory. This factor analysis was conducted using Maximum Likelihood (ML) and Varimax rotation. Second-order factor analysis was conducted to identify the factors of travelers' willingness to buy and use EVs. Third-order factor analysis identified the factors concerning perceived social and economic values and personal preferences in traveling. The reliability of the factors and internal consistency among respondents in the evaluation were examined with the help of factors' Cronbach's alpha values. Cronbach's value of more than 0.7 shows an acceptable level of reliability and a value of above 0.5 shows a moderate level of reliability [76, 77]. The results of factor analyses were combined to develop a structural model. This structural model was developed using SPSS Amos software. This software takes a confirmatory approach to construct the measurement equations and structural equations. Again, the ML method was used to develop this comprehensive structural model. The measurement models determine the correlations between observed variables and latent variables (factors). Measurement models are combined to identify significant structural equations between latent variables. In this study, observed variables of travelers' personal and trip characteristics were identified and included in the model to assess their impact on PN and willingness to buy and use EV. These variables were coded on a binary scale, that is, 1 or 0. The reliability of the structural model was determined and checked by comparing the values of the ratio of chi-square to the degree of freedom (CMIN/DF), the goodness of fit index (GFI), adjusted goodness of fit index (AGFI), comparative fit index (CFI), and root mean square error of approximation (RMSEA). The recommended value of CMIN/DF is 2–5; GFI, AGFI, and CFI should be greater than 0.9; and RMSEA needs to be less than 0.08 [72, 78, 79].

3.5. Research Hypothesis. Figure 1 presents the framework of the research hypothesis of this study. It was hypothesized that people's awareness about the consequences and sense of responsibility for the negative outcomes of their travel behavior influences the development of personal norms. The AC and AR are correlated with each other. The PN has a direct influence on people's willingness to buy and use the electric vehicle and it may also play the role of a mediator to explain the influence of AC, AR, and other defined variables of social and economic values and personal preferences on willingness to buy and use the EVs. It was hypothesized that perceived social and economic values and traveler's personal preferences in traveling may also have significant direct effects on travelers' willingness to buy and use the EVs, and willingness to buy may directly influence the users' intentions to use the EV. This study also assumed that the personal and travel characteristics of travelers may have a significant direct correlation with the PN and indirect influence on willingness to buy and use the EVs through the PN as a mediator.

4. Data Analysis and Results

4.1. Descriptive Statistics of the Respondents. The descriptive statistics show that the share of male and single respondents is more in the sample (Table 2). The share of the female working population is quite less in Lahore, resulting in their low share in the model split of Lahore, which justifies the low share of female respondents in the sample. The share of young respondents is high as around 65% of them are below the age of 30 years. The young people also make a high proportion of the overall population of Lahore city, so it is believed that this age distribution of the sample is consistent with the population. Students have a major share in the sample followed by employees. Most of the respondents fall into the low-income category, which is due to the presence of students in a large proportion in the sample. Around 45.27% of the respondents own one or more than one car. The model split shows that motorcycle, private car, and public transport modes have shares of 28.61%, 33.83%, and 12.94%, respectively. More than 70% of the respondents have a trip frequency of 5-6 days a week or higher. The trip length distribution is also presented in Table 2.

4.2. Factor Analysis and Average Responses. A factor analysis was conducted on collected responses regarding PN, AC, and AR variables of the NAM theory. This factor analysis confirms the association of observed variables with their corresponding latent variables, that is, AC, AR, and PN, as shown in Table 3. Average responses of each indicator are also presented in Table 3. The estimated values of Cronbach's

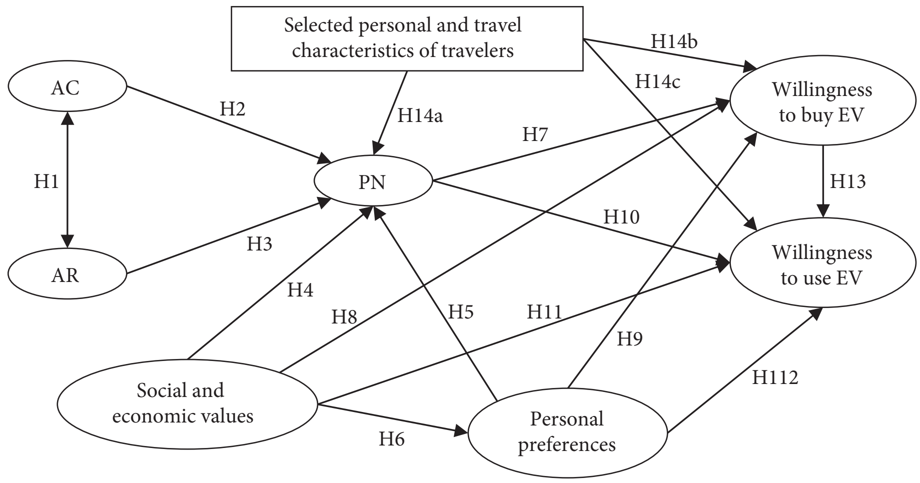

Figure 1: Framework of research hypothesis (AC: awareness of consequences, AR: ascription of responsibility, and PN: personal norm).

Table 2: Descriptive statistics of the respondents' SEDs.

Characteristics	Distribution (%)
Gender	Male (85.6), female (14.4)
Marital status	Single (66.9), married (33.1)
Age (years)	Below 20 (30.8), 21–30 (35.8), 31–40 (16.2), 41–50 (11.2), above 50 (6)
Education	High school or below (21.4), higher secondary/diploma (25.1), bachelor (38.3), master's or higher (15.2)
Profession	Students (38.3), employees (28.4), business (12.9), others (20.4)
Income	≤20,000 (43.8), 21,000–30,000 (10.2), 31,000–40,000 (8.2), 41,000–60,000 (11.7), 61,000–80,000 (8.2), >81,000 (17.9)
Car ownership	None (54.7), 1 (35.57), 2 (7.5), more than 2 (2.2)
Car driving license	Yes (37.3), no (62.7)
Usual travel mode	Walk/bicycle (9.9), private car (33.8), motorcycle (28.6), auto rickshaw/taxi (8.5), campus/office transport (6.2), public transport (12.9)
Trip frequency per week	Almost every day (57.9), 5-6 days (16.7), 3-4 days (15.2), 1-2 days (4.7), a few times a month (5.5)
Trip distance (km)	< 10 km (52.4), > 10 km (47.6)

Table 3: Rotated factor loadings of the NAM variables.

Observed variables	Mean	Factor		
		PN	AR	AC
I feel morally responsible for the betterment of the urban environment and society (PN-1)	4.025	0.793		
I feel a moral responsibility to preserve natural resources such as oil and gas (PN-2)	4.094	0.669		
I feel joint responsibility for the consumption of natural resources such as oil and gas (AR-1)	3.985		0.946	
I feel equal responsibility for the degradation of the environment due to an increase in traffic (AR-2)	4.014		0.495	
Excessive use of gasoline/diesel cars deteriorates (destroys) the urban quality of life and environment (AC-1)	3.992			0.875
Car usage causes a shortage of scarce (rare) natural resources, for example, oil and gas (AC-2)	4.025			0.494
Percentage of variance explained		21.678	20.561	17.512
Cronbach's alpha		0.737	0.715	0.673

alpha are more than 0.7 for PN and AR variables, whereas the value for the AC variable is near 0.7. The percentages of variance explained by PN, AR, and AC are 21.678, 20.561, and 17.512, respectively. These values show an acceptable level of reliability of these variables and internal consistency among respondents in the evaluation. The variable PN shows that the respondents placed high beliefs on their moral obligations for the betterment of the urban environment and society, as well as preservation of natural resources. The factor of AR depicts travelers' mutual sense of responsibility for the consumption of resources and degradation of the environment due to increased traffic demand. Also, the travelers have a good sense of awareness concerning negative outcomes of their behavior such as deterioration of urban quality of life and environment due to air pollution and reduction of natural resources due to use in transportation. It is believed that the travelers' sense of awareness and responsibility and moral obligations would have a significant influence on their intentions to buy and use an EV.

Second-order factor analysis was conducted on respondents' responses concerning their willingness to use EV (Use) and willingness to buy EV (Buy). Cronbach's alpha values were estimated for both factors as presented in Table 4. The calculated alpha values are more than 0.7, which predicts an acceptable level of reliability of the factors and internal consistency among respondents in the evaluation of the observed variables. Most of the respondents are willing to use EVs for the preservation of natural resources, to reduce air pollution, and for the availability of cheap electricity. The results of the factor willingness to buy show that the targeted groups of travelers have high willingness to buy an EV provided that they have better awareness about the mileage of EVs, low initial and maintenance costs than oil/diesel cars, and batteries with long life. The results of factor analysis predicted positive attitudes, norms, and intentions of travelers towards the use and ownership. The percentages of variance explained by both factors are 24.977 and 22.810, respectively.

A third-order factor analysis was conducted on perceived social, economic, and personal aspects of traveling. This exploratory factor analysis resulted in two factors, that is, personal preferences (PP) and social and economic values (SEV). The estimated Cronbach's alpha values are more than 0.5, which shows a moderate level of reliability of the extracted factors. The PP factor depicts travelers' priorities in vehicle ownership and use of electric vehicles within a city as it is easy to charge the vehicle. The first observed variable in the PP factor has more influence in explaining the factor as it has high factor loading. In the SEV factor, the observed variable of "I prefer to drive a fuel-economical vehicle" has more impact on the SEV factor as it has a very high factor loading. It also shows that there are travelers who feel socially responsible to save the environment. The percentages of variance explained by PP and SEV are 21.282 and 21.082, respectively, as described in Table 5.

4.3. Structural Equation Modeling (SEM). A structural model was developed using the results of factor analysis. This model tested the stated hypothesis of Figure 1. Observed variables of travelers' socioeconomic demographics (SED) variables were defined as binary variables and tested for possible significant structural relationships with variables of PN, willingness to buy, and willingness to use EV. Various variables were defined and tested but here only significant variables are presented and discussed. These variables included profession (1 if travelers are employees and 0 otherwise), age (1 if age is less or equal to 30 years and 0 otherwise), travel mode (1 if the mode is a motorcycle and 0 otherwise), car ownership (1 if owning one or more cars and 0 otherwise), income (1 if income is between 21,000 and 60,000 and 0 otherwise), and trip distance (1 if the distance is more than 10 km and 0 otherwise).

The results of measurement and structural equations are presented in Figure 2. The rectangles and ellipses or circles in Figure 3 define the observed variables and latent variables, respectively. This structural model shows that all the measurement equations are positive and significant at a 1% or 5% level of significance. The AC and AR latent variables have a positive and significant association which depicts that the respondents who have awareness about negative outcomes also possess a sense of responsibility for the outcomes of their behavior. The structural coefficients of AC and AR with PN are positive and significant at a specific significance level. The significance and prediction power of these relationships are consistent with previous studies explaining sustainable travel behavior [51, 54, 56, 80]. These significant equations show that the travelers who have a sense of awareness and responsibility about negative outcomes of their behavior also felt a moral obligation to preserve the natural resources and for the betterment of the urban environment and society. The SEV variable has a positive and significant structural coefficient with the PN which predicts that the travelers who put high beliefs on social and economic values in traveling felt morally obliged to protect the environment and society and to preserve the natural resources. The young travelers (≤30 years), civil and private employees, trip distance (>10 km), and motorcycle users have positive structural relationships with the PN, whereas travelers with an income level of 21,000–60,000 PKR have a negative coefficient with the PN. Other researchers have also shown the significance of age, income, and profession in EV adoption behavior [34, 35]. These results show that the employees, young travelers, motorcycle users, and travelers with a trip distance of more than 10 km have high moral obligations, whereas the travelers who fall in mentioned income range have low moral obligations. The AC, AR, and SEV along with age, income, travel mode, profession, and trip distance variable explain almost 48% of the variance in the PN. The SEV and PP variables are positively related to each and significant at a 10% level of significance. It is shown that the travelers' perceived economic and social value influences their priorities in traveling and vice versa.

The structural equations of PN and PP with the willingness to buy and use an EV are significant and positive, which depicts that the development of prosocial norms among travelers and individual's priorities in traveling significantly influence the potential of EV ownership and usage. These results are in agreement with a significant role of problem awareness and personal norms in travelers' willingness to adopt sustainable transport policies [51, 56, 81]. The respondents who are employees and own a car also developed positive correlations with the willingness to buy an EV, and the variable of car ownership is also significant with willingness to use an EV. It means present car owners, and civil and private employees have a high propensity to own an EV in the future. The PN, PP, employees, and car ownership variables explain almost 67% of the variance in willingness to buy. Similarly, the variables of PN, PP, and car ownership collectively explain almost 32% of the variance in willingness to use. The PN variable also explains the role of the mediator to explain the indirect influence of AC, AR, and SEV on travelers' willingness to buy and use an EV. The PP variable is also a mediator between SEV and willingness to buy and use. The values of

Table 4: Rotated factor loadings of willingness to buy and use EV.

Observed variables	Mean	Factors	
		Willingness to use EV (Use)	Willingness to buy EV (Buy)
I am willing to use an electric vehicle for the preservation of natural resources (Use-1)	3.880	0.868	
I am willing to use an electric vehicle to reduce air pollution in the city (Use-2)	3.972	0.758	
I am willing to use an electric vehicle considering the availability of cheap electricity (Use-3)	4.037	0.534	
I would buy an electric vehicle if I have more information about the mileage with one-time charging (Buy-1)	4.082		0.776
I would buy an electric vehicle if the initial purchase cost is less than petrol or diesel vehicles (Buy-2)	4.164		0.588
I would like to buy an electric vehicle if the maintenance and battery costs are less than petrol or diesel cars (Buy-3)	4.206		0.542
I would like to buy an electric vehicle if the charging batteries have a long life (Buy-4)	4.278		0.437
Percentage of variance explained		24.977	22.810
Cronbach's alpha		0.786	0.702

Table 5: Rotated factor loadings of extracted factors.

Observed variables	Mean	Factor	
		Personal preferences (PP)	Social and economic values (SEV)
I like to have a car with a small engine capacity (e.g., below 1000 liters = 1.0 liters) (PP-1)	3.120	0.780	
Having an electric vehicle is a status symbol for me (PP-2)	3.381	0.445	
I would prefer to use an electric vehicle only within a city as it is easy to get charge of it (PP-3)	3.955	0.371	
I prefer to drive a fuel-economical vehicle (SEV-1)	4.281		0.939
I consider it as my social responsibility to save the environment (SEV-2)	4.527		0.383
Percentage of variance explained		21.282	21.082
Cronbach's alpha		0.515	0.508

the goodness of fit parameters fall within the recommended limits or near to the limits; for example, CMIN/DF lies in the range of 2–5, GFI and AGFI are more than 0.8, and RMSEA is less than 0.08. These values show that this structural model has an acceptable level of reliability in explaining the travelers' potential to own and use an EV under the framework of NAM theory. Table 6 shows the significance of the defined hypothesis. The significant hypotheses are mentioned as supported and insignificant hypotheses are stated as not supported. The hypotheses between PP and PN, between SEV and willingness to buy, and between SEV and willingness to use were not supported by the collected data. Only significant hypotheses of defined variables SEDs with PN, willingness to buy, and willingness to use are presented.

5. Discussion and Policy Implications

With the rapid increase in the population and inadequate public transport systems, Pakistan is becoming more dependent on conventional (gasoline) vehicles which jeopardize environmental sustainability, especially in urban areas. During the last few years, smog has severely hit the major cities in the winter, which is compelling the governments to close educational institutes and summer leads to severe heat waves which are causing many deaths each season [10]. Therefore, it is a national priority to improve the transport sectors which include the diversification of fuel towards sustainable and renewable energy resources. For road transportation, EVs are one of the very efficient energy alternatives to conventional vehicles. The respondents of this study manifested a positive attitude towards the adoption of EVs owing to their prosocial and proenvironmental behavior; a conceptual framework of derived EV behavioral intervention techniques is shown in Figure 3. This framework shows that the travelers' sense of awareness and responsibility about the negative outcomes of their behavior is essential to develop prosocial personal norms among them. It implicates that better awareness of travelers about environmental problems caused by conventional vehicles emissions and preservation of natural resources can play a predictive role in improving moral obligations for the betterment of the urban environment and society. The sense of social and economic values in traveling also has significant correlation with the travelers' moral obligations to protect the environment and save natural resources. The presence of these social norms and values and sense of responsibility among travelers can be handy in the promotion of environmentally friendly vehicles such as EVs. For this purpose,

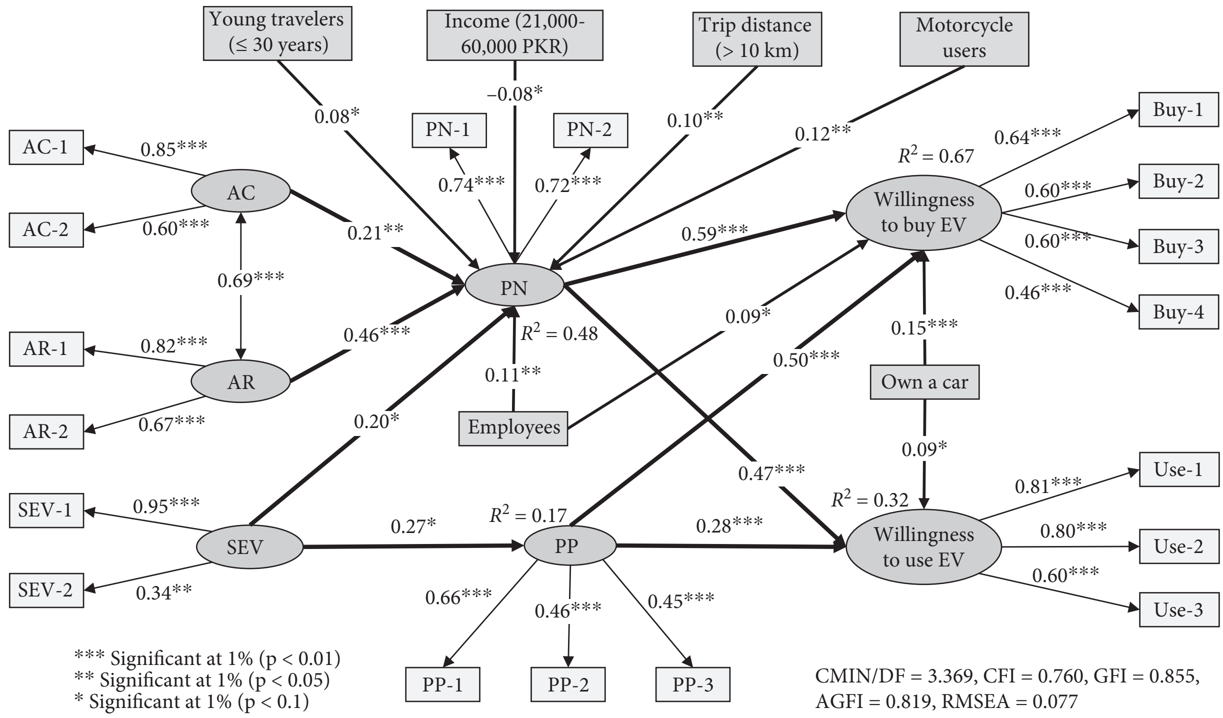

Figure 2: Structural model of travelers' willingness to buy and use an electric vehicle (AC: awareness of consequences, AR: ascription of responsibility, PN: personal norm, SEV: social and economic value, PP: personal preferences, CMIN/DF: chi-square/degree of freedom, CFI: comparative fit index, GFI: goodness of fit index, AGFI: adjusted goodness of fit index, and RMSEA: root mean square error of approximation).

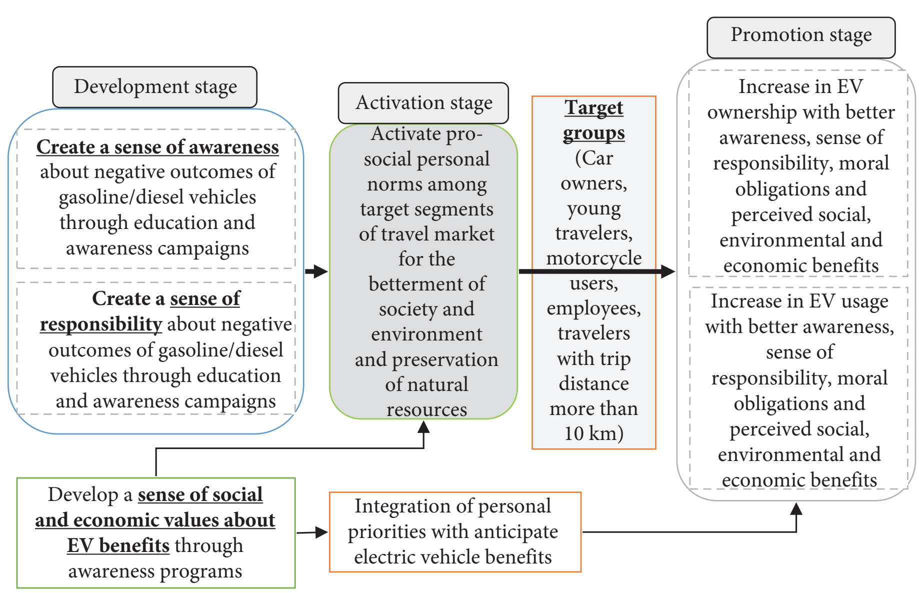

Figure 3: A conceptual framework of behavioral interventions to promote the EVs.

it is required to initiate appropriate awareness and education programs to highlight the benefits of EVs and disadvantages of gasoline/diesel vehicles among travelers. There is also a need to activate the sense of responsibility among travelers through education, seminars, and awareness as it will help to save the environment and natural resources and to enhance the purchase behavior of customers [82]. Once the travelers have better awareness about the economic and social benefits of EV, they would prefer to shift to sustainable vehicle technologies to protect the urban environment and society from severe air pollution resulting from the transportation sector. This favorable attitude of an individual towards environmental issues is more likely to be a compelling reason to purchase EV. The activation of person norms and integration of personal priorities with EV benefits would help in promoting EV ownership and usage for the target

Table 6: Results of hypothesis significance.

Hypothesis	Hypothesis description			Decision
H1	AC ↔ AR			Supported
H2	AC ⟶ PN			Supported
H3	AR ⟶ PN			Supported
H4	SEV ⟶ PN			Supported
H5	PP ⟶ PN			Not supported
H6	SEV ⟶ PP			Supported
H7	PN ⟶ willingness to buy EV			Supported
H8	SEV ⟶ willingness to buy EV			Not supported
H9	PP ⟶ willingness to buy EV			Supported
H10	PN ⟶ willingness to use EV			Supported
H11	SEV ⟶ willingness to use EV			Not supported
H12	PP ⟶ willingness to use EV			Supported
H13	Willingness to buy ⟶ EV willingness to use EV			Not supported
H14a	Motorcycle users, young travelers, employees, trip distance >10 km, middle income	⟶	PN	Supported (only significant equations are reported)
H14b	Own a car, employees	⟶	Willingness to buy EV	Supported (only significant equations are reported)
H14c	Own a car	⟶	Willingness to use EV	Supported (only significant equations are reported)

groups of the travel market as shown in Figure 3. The identified target groups of the travel market would possess the required potential to purchase and use an EV considering associated prosocial, environmental, and economic benefits [34]. The selection of appropriate target groups is very important for crafting energy and transport policies and for the inclusion of EV policies as a success. The main target groups can be present car owners and motorcycle users, civil and private employees, and young travelers who have the potential to own a car in the future. Also, there is a need to provide required economic and infrastructure incentives on EVs ownership and usage. These incentives include subsidies, cheap electricity, low registration taxes, tradable permit schemes, and the availability of charging stations [83, 84]. Therefore, it is required to develop a system to provide necessary information about spatial coverage of charging stations as it will help to attract potential buyers and users of EVs [12]. Awareness of travelers about available economic, social, and accessibility incentives is an important policy to enhance the adoption behavior of the masses. For this purpose, awareness campaigns through electronic, print, and social media can be initiated to create awareness about the benefits of EVs. The sense of awareness and responsibility and activation of moral obligations would help in promoting EV ownership and usage. In this regard, the government and other social organizations should join forces and work in close collaboration to create awareness and improve the understanding of the potential customers about how conventional vehicles are the main contributing factor towards deteriorated air quality in the main cities. The change in the adoption behavior of travelers will help in alleviating the environmental problems in Lahore city and other developing regions. It is believed that there would be an increase in the purchasing and adoption behavior of EVs if these policy measures are implemented with utmost effort. The government should encourage private auto market to launch EVs in the country by providing special subsidies and reducing taxes. The government's financial incentive programs for the auto industry and its users would help in developing green transport infrastructure in the country. The private companies should initiate the installation of charging stations along major highways and at other key points to facilitate the potential users of EVs. It is required to deploy special marketing strategies to educate the travelers regarding availability of cheap EV and associated benefits and facilities such as location of charging stations. A proper contribution from the private sector is important in promoting the use of EVs in developing countries. However, proper financial and administrative support from the government is also vital in this regard. Electric mobility can be integrated with ridesharing and DRT to reduce the environmental impacts of transportation infrastructure. Special economic incentives to the riders of EVs in combination with car-sharing and DRT can help to shape the cities' transport sustainably.

6. Conclusion

This study identified behavioral interventions for the promotion of EVs using the results of a questionnaire survey. The framework of the NAM theory was extended including personal and travel characteristics, as well as perceived economic and social values and personal priorities in traveling. The factor analysis confirmed the correlations of questionnaire statements with AC, AR, and PN according to the NAM theory. The other extracted factors also have an acceptable level of reliability in explaining the EV adoption behavior. The AC, AR, and SEV factors are significant and positive predictors of the PN. The PN and PP factors are strong predictors of travelers' willingness to buy and use an EV. The young travelers, motorcycle users, employees, and trip distance are positively related to their moral obligations, whereas the income group (21,000–60,000 PKR) has a negative correlation with the PN. The PN variable also plays a role of a mediator to explain the influences of AC, AR, and SEV variables on willingness to buy and use EVs. The travelers' willingness to buy and willingness to use EVs are positively influenced by their present car ownership status.

The findings implicate that the development of a sense of awareness and responsibility about the negative outcome of their behavior would help in activating the prosocial norms among travelers for the betterment of the urban environment and society and preservation of natural resources. Similarly, travelers' awareness regarding economic, social, and environmental benefits associated with the use of EVs would help to develop positive personal norms among travelers. The current car owners, young travelers, current motorcycle users, and employees can be target groups of the travel market for this promotion. The availability of charging stations, cheap electricity, and economic incentives from the government in terms of tax relaxation and subsidies would be handy pull measures to alter the adoption behavior. On a broader scale, this study aims to contribute to the efforts of the government in maintaining a more sustainable transport infrastructure in Lahore city, where energy and transport policies are needed to be urgently integrated and special efforts are required to understand the motivations of the customers to understand their purchasing behaviors towards EVs.

The sample of this study mainly comprised young people and students, which may cause bias in the extracted findings and policy implications. Future studies should focus on large samples consisting of adequate representation of different groups of the travel market. Also, the policies derived from stated preferences studies may be biased as the actual intentions of the travelers may differ once the relevant policy is implemented. Therefore, further studies are required after the implementation of the EV policy to examine the actual preferences of travelers. Those studies should also evaluate the influence of charging stations accessibility, electricity price, and spatial coverage of charging stations, as well as mileage with one-time charge of electric batteries on traveler's willingness to use the EVs. Despite limitations, the findings of this study would provide useful insight into significant behavioral interventions to promote the EVs and reduce the environmental issues.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

The authors authorize the MIUR to reproduce and distribute reprints for governmental purposes, notwithstanding any copyright notations thereon. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the MIUR.

Conflicts of Interest

The authors declare no conflicts of interest.

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