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Stochastic Operational Driving Cycles of an Electric Vehicle Battery System for Degradation Experiments

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ABSTRACT

This study proposes a novel framework for designing battery degradation experiments. The proposed framework aims to evaluate the lifetime of a lithium-ion battery (LIB) pack in electric vehicles (EVs) under stochastic operational conditions by comprising two phases. First, the consumption scenario is established through an in-depth analysis on the charging characteristics of EVs under various road types. This scenario aims to replicate the actual charging and discharging processes based on the daily battery consumption patterns of EVs. Second, an operational profile is generated to represent the driving characteristics of the LIB pack in EVs through two steps. Specifically, the first step generates a virtual speed profile to represent the dynamic characteristics of EVs under stochastic operational conditions. The second step then converts this speed profile into a discharging current profile in consideration of the mechanical and electric characteristics of the EVs. Comprehensive analysis on the operational profiles generated using actual driving data demonstrates the representativeness and high fidelity of the proposed framework. The degradation experiment with the proposed framework further confirms the time efficiency in that the proposed framework achieves 2.94 times higher efficiency in terms of time and labor consumption compared with the field experiment. This achievement suggests that the proposed framework could serve as a novel tool for designing battery degradation experiments that replicate the stochastic operational conditions of EVs.

1 | Introduction

Interest in new transportation systems is rising to alternate conventional vehicles with an internal combustion engine because concerns on global warming and climate change continue to intensify [1, 2]. Electric vehicles (EVs) have recently been regarded as the next-generation mobility systems in the automobile industry, not only for their improved transportation performance and efficiency but also for their capability to address greenhouse gas emissions [3, 4]. Despite these benefits, concerns about the safety and reliability of EVs are gradually being

exposed with the continuous growth of EVs in the market [5]. In particular, the lifespan of lithium-ion batteries (LIBs), which serve as the power sources of EVs, remains a significant concern because LIBs degrade over time and under operational conditions [6, 7]. Specifically, the degradation phenomenon of LIBs inevitably occurs during actual operation, resulting in performance and lifespan deterioration [8]. This irreversible degradation is triggered by stochastic operations that act as stress factors, resulting in various issues related to the performance and safety of EVs, including capacity loss, internal resistance increase,

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and power fade [9–15]. Hence, a quantitative evaluation of the long-term degradation of LIBs is indispensable to ensure the reliable operation of EVs.

Extensive degradation experiments have been conducted to evaluate the lifespan of LIBs deployed in EVs [16, 17]. In particular, two main approaches have been addressed for analyzing the degradation behavior of LIBs, including postmortem analysis and battery degradation experiments. Specifically, aged batteries in EVs were disassembled for postmortem analysis of the main components, including the electrolyte and negative electrode, because this approach would be effective for elucidating the degradation pathways of the main components in EVs under actual operational conditions [18]. However, this approach has a critical limitation in that the accumulated degradation could only be elucidated at the final endpoint. Hence, postmortem analysis has difficulty in characterizing the degradation pathways of LIBs in EVs because of the limitations in tracking the full degradation pathway of LIBs during actual operation. This limitation could be addressed by examining degradation experiments that repeatedly apply static charging and discharging cycles, which commonly use constant-current (CC)-based profiles [19]. This approach enables the quantitative tracking of full degradation pathways over cycles using the Coulomb-counting method [20]. Hence, this approach would be effective for analyzing the influence of operational conditions on the dependency of the degradation pathways of LIBs because this approach could account for environmental conditions, including depth of discharge (DOD), C-rate, and ambient temperature [21, 22]. However, this approach inherently struggled with fundamental limitations regarding the path dependency of degradation characteristics [23–26]. Specifically, the application of static cycling conditions in laboratory experiments fails to adequately capture the highly versatile and dynamic load characteristics of EV's actual operation, including rapid alternation of deintercalation and intercalation processes [27]. This limitation suggests that a novel experimental approach would be necessary to account for the dynamic and stochastic operational conditions in field environments.

Driving cycles have been actively studied to design effective degradation experiments for LIBs in EVs. These studies have aimed to develop a convenient means of replicating actual driving conditions in laboratory environments [28, 29]. In particular, stochastic driving cycles have garnered significant attention because these methods are capable of representing various actual operational conditions [30]. Note that stochastic driving cycles enable the effective evaluation of LIB degradation under the actual dynamic operational conditions of interest [31]. Specifically, modal driving cycles, including New European Driving Cycle (NEDC) [32] and Japanese 10 mode (J10) [33], were proposed to reflect typical driving patterns based on combinations of virtual constant driving phases, such as idling, acceleration, and cruising. However, these driving cycles have limitations in sufficiently reflecting driving patterns of field driving measurements [34]. Transient driving cycles, including World-wide harmonized Light duty Test Cycle (WLTC) [35] and the Federal Test Procedure (FTP-75) [34], were proposed to address these limitations based on field driving measurements, thereby enabling the reflection of comprehensive driving conditions across various regions worldwide. These driving cycles enable the analysis of the influence of actual operation conditions on LIB degradation [36].

However, the main lack of these methods is their insufficient representation of driving conditions in targeted road environments [37]. This problem would be attributed to several factors, including the traffic conditions of a given area, driving behavior, and the characteristics of vehicles. As an alternative, field driving cycles acquired directly from data loggers installed in EVs have been used as load profiles for battery degradation experiments [38]. These field driving cycles are extracted directly from raw field driving data, thereby enabling the direct imposition of battery loads under actual operational conditions, including ambient temperature and traffic conditions. However, field driving cycles have limitations in fully replicating the actual driving characteristics of the LIB pack in EVs because of uncontrollable factors in various road environments [39]. These limitations suggest that further research toward advanced methods is demanded to address the lack of sufficient replication of the actual driving characteristics of EVs.

Significant efforts have recently been devoted to studying advanced driving cycles that represent actual driving conditions in various road environments [40, 41]. Specifically, stochastic driving cycles have been generated based on a state transition matrix derived from driving pattern analysis, enabling performance evaluation under specific driving conditions by ensuring representativeness through the validation of statistical driving characteristics. Recent studies on the performance evaluation of LIBs especially, have focused on generating virtual speed profiles that represent actual operational conditions [42]. However, the systematic methods for converting these profiles into current profiles remain insufficient for degradation experiments. Note that a conversion method for the accurate estimation of a current profile is essential because the actual voltage of the LIB pack dynamically varies with the state of charge (SOC) and C-rate [37]. Note also that inaccurate conversion might result in a significant underestimation or overestimation of the actual voltage under extreme operational conditions, including high SOC and high C-rate. Therefore, further research is needed to systematically convert the speed profile into the current profile for battery degradation experiments.

To overcome the limitations aforementioned, this study proposes a novel framework for designing stochastic degradation experiments for LIBs in EVs. Note that the proposed framework aims to accurately replicate the actual dynamic operational conditions of EVs in consideration of various design factors, including charging and discharging patterns, SOC ranges, and dynamic battery loads. The novelty and key contributions of this study are summarized as follows:

- The proposed framework extracts the optimal consumption patterns from actual various road types, including the SOC range and charging frequency, establishing stochastic degradation experimental procedures tailored to specific road conditions for each implementation. Hence, the proposed framework can account for the uncertainty and variability of the actual operational conditions, thereby generating a virtual yet realistic degradation pathway of LIBs in EVs.
- The state transition matrix and four-generation rules are addressed for designing a novel stochastic generation method so that the proposed method can generate the virtual speed profile that represents the dynamic driving

characteristics under various road types. Bayesian optimization (BO) is further employed to optimize the relative importance of dynamic driving characteristics. Note that this approach effectively integrates a stochastic generation method for the speed profile and optimization theory, enabling the generation of multiple speed profiles that replicate actual stochastic driving conditions in a laboratory environment.

- High fidelity mechanical-dynamics models and power efficiency are addressed for establishing a systematic conversion method so that the generated speed profiles can be accurately converted into the corresponding current profiles. This approach integrates elaborate torque estimation in consideration of virtual road slope and power efficiency, reflecting the direction of the current flow.
- Systematic analysis and quantitative comparison with actual driving data reveal the operational fitness and generality of the proposed framework. The degradation experiment with the proposed framework further confirms the improved efficiency compared with that of field experiments in terms of time and labor considerations.

The remainder of this paper is organized as follows: Section 2 analyzes the characteristics of the actual durability driving test data. Section 3 provides a detailed explanation of the construction of the scenario for the degradation experiments and the procedure for generating the operational profiles required for the discharging process. Section 4 presents the implementation of the proposed framework and validates the superiority of the proposed framework by evaluating operational fitness and time efficiency. Finally, Section 5 concludes the study by summarizing the discussions and future works.

2 | Field Driving Data

Driving data for two EVs were obtained from actual durability driving tests. The detailed specifications of the two EVs used in these tests are summarized in Table 1. Note that the specific model of the EVs is confidential due to a nondisclosure agreement (NDA) with the company that examined the durability of the driving tests. In brief, both EVs share the same configuration of a powertrain but have different vehicle architectures, resulting in slight differences in dynamic characteristics such as weight, gear ratio, and aerodynamics. Both EVs also equip the LIB pack containing the same type of nickel manganese cobalt oxide (NMC) cells, but the pack design of each EV would be different significantly. Specifically, the LIB pack of EV #1 comprises 22 series-connected LIB modules with a voltage of 21.8 V, resulting in a total pack voltage of 480 V and a power-rated capacity of 53.0 kWh, whereas that of EV #2 comprises 32 series-connected LIB modules with a voltage of 21.8 V, resulting in a total pack voltage of 697 V and a power-rated capacity of 77.4 kWh. This difference suggests that the two EVs might have different energy and power management strategies because of their different electric characteristics. Specifically, EV #1 features voltage regions from 369.4 to 554.4 V for the full SOC region from 0% to 100 % (Figure 1a), whereas EV #2 features voltage regions from 537.3 to 806.4 V for the same SOC region (Figure 1b). Note that this difference in the voltage range would originate from the number of series connections in LIB modules. Note also that the pack-level OCV is

estimated from the OCV measured from the LIB module, considering the series configuration of each EV. The details on OCV measurements for the LIB module and the estimation of the pack-level OCV are provided in Appendix A. The details of the test environments, dynamic driving characteristics, electrical driving characteristics, and charging characteristics of the EVs are provided in the following subsections.

2.1 | Test Environments

Driving data such as speed, acceleration, and revolutions per minute (RPM) were collected from the two test vehicles during actual durability driving tests on six different routes categorized into three road types: urban, rural, and highway (Figure 2). Note that the detailed information about the driving routes is confidential due to the NDA with the company. In brief, urban is defined as an arterial, collector, and local road inside and/or near a central business district (CBD), with a speed limit ranging from 40 to 80 km/h [35]. Rural is defined as the arterial, collector, and local road inside nonurban areas, with a speed limit ranging from 50 to 80 km/h. A highway is defined as a high-speed road connecting urban and rural roads, with a speed limit ranging from 100 to 120 km/h. These roads were selected to represent high-usage driving scenarios under actual operational conditions [35]. Note that the test vehicles were driven along fixed routes for each road type, whereas the driving characteristics varied depending on uncontrollable environmental factors such as the driver, driving duration, weather, and daily traffic, implying the presence of variability each time [45]. Driving data were collected through the controller area network (CAN), including both dynamic and electrical responses (Table 2). Note that each controller, including the electronic stability control (ESC), the motor control unit (MCU), and the battery management system (BMS), manages a distinct embedded system, and the sampling intervals vary depending on the response. The test periods were over 2 months for EV #1 from July to August 2024, whereas they were over 10 months for EV #2 from December 2022 to September 2023. Notably, the scope of the durability test data collected for each test vehicle varied, resulting in differences in the data volume. Specifically, the driving data corresponding to the durability driving test on EV #1 were collected for the full test with a mean duration of 162.21 h, whereas the driving data corresponding to the durability driving test on EV #2 were collected only for partial segments with a mean duration of 4.82 h. In addition, the charging data corresponding to the durability driving test on EV #1 were partially collected during the mid-driving and postdriving charging events. The partially collected charging data were considered sufficient to identify representative charging trends and operational charging patterns for designing the degradation experiments. This is because charging events are performed based on relatively static protocols and procedures. In contrast, the driving data are substantially affected by various uncontrollable environmental factors, and thus, a sufficient volume of measurements is required to reflect the stochastic variability under actual operational conditions.

2.2 | Dynamic Driving Characteristics of EVs

This subsection describes the dynamic driving characteristics obtained from the actual durability driving tests of EV #1

TABLE 1 | Specifications of the two EVs [43, 44].

Test vehicle	Parameter	Symbol	Value	Unit
EV #1	Wheel radius	R	0.2286	m
	Gear ratio	gr	4.471	—
	Vehicle mass	m	1800	kg
	Rolling resistance coefficient	μ	0.01	—
	Gravitational acceleration	g	9.81	m/s ²
	Air density	ρ_{Air}	1.225	kg/m ³
	Frontal area	A_f	2.8106	m ²
	Aerodynamic drag coefficient	C_D	0.21	—
	Power efficiency	η	90	%
	LIB type	—	NMC	—
	Nominal voltage	V	480	V
	Power-rated capacity	E	53.0	kWh
	Nominal capacity	Q	111.2	Ah
	Series configuration	N_s	22	—
EV #2	Wheel radius	R	0.2413	m
	Gear ratio	gr	4.706	—
	Vehicle mass	m	1945	kg
	Rolling resistance coefficient	μ	0.01	—
	Gravitational acceleration	g	9.81	m/s ²
	Air density	ρ_{air}	1.225	kg/m ³
	Frontal area	A_f	3.0334	m ²
	Aerodynamic drag coefficient	C_D	0.288	—
	Power efficiency	η	90	%
	LIB type	—	NMC	—
	Nominal voltage	V	697	V
	Power-rated capacity	E	77.4	kWh
	Nominal capacity	Q	111.2	Ah
	Series configuration	N_s	32	—

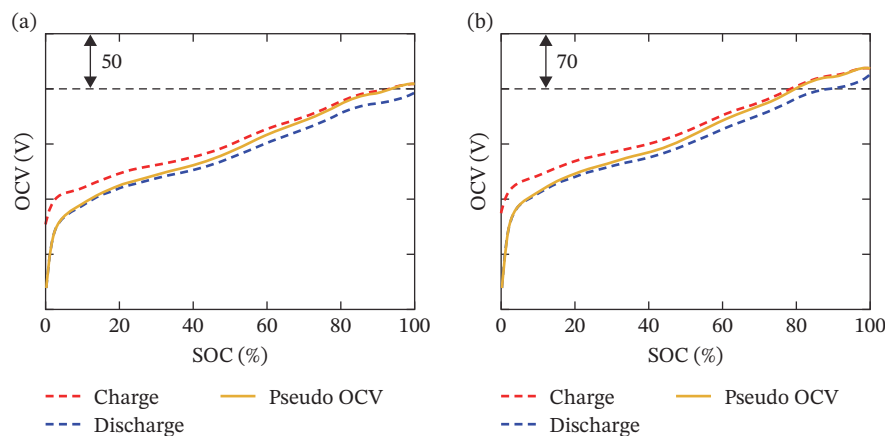


FIGURE 1 | Pack-level OCV for (a) EV #1 and (b) EV #2.

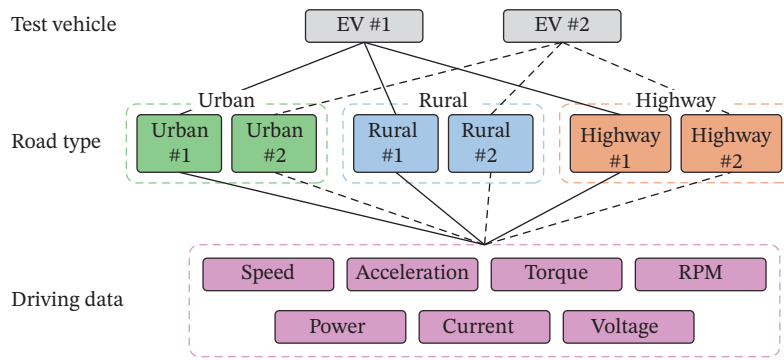


FIGURE 2 | Summary of collected EV driving data.

TABLE 2 | Information on driving data obtained from actual durability driving test.

Response	Controller	Sampling interval (s)	Unit	Description
Speed	ESC	0.03	km/h	Vehicle speed
Acceleration	ESC	0.01	m/s ²	Vehicle acceleration
Torque	MCU	0.13	Nm	Motor torque
RPM	MCU	1.00	rad/min	Motor RPM
Current	BMS	0.10	A	LIB pack current
Voltage	BMS	0.10	V	LIB pack voltage
Power	BMS	0.10	kW	LIB pack power

(Figure 3a) and EV #2 (Figure 3b). The measured speed and acceleration vary across urban (the left column in Figure 3), rural (the middle column in Figure 3), and highway (the right column in Figure 3), resulting in differences in the torque and RPM of the motors deployed on the EVs. Remarkably, notable differences are observed in the dynamic driving characteristics depending on the road type (Table 3). Specifically, the mean speeds of the EVs based on the driving data are 25.69, 45.02, and 99.45 km/h in urban, rural, and highway road types, respectively, suggesting that the mean speeds of both EVs increase from urban to rural and further on the highway. The mean speed is regarded as a representative dynamic driving characteristic because mean speed directly reflects the operational speed range of each road type. Note that the 95% confidence interval (CI) of the mean speed across road types is separated by distances ranging from 8.93 to 47.76 km/h for both EVs, thereby substantiating statistically distinct differences in the dynamic driving characteristics across road types. Moreover, the mean acceleration and deceleration are the highest in the type of urban road at 0.63 and -0.58 m/s², decreasing in the order of rural to highway. This analysis suggests that vehicles operate at the highest speeds in the type of highway road, whereas speed variations would be the most significant in the type of urban road. Note that the analysis on the frequency of repeated driving behaviors, including stopping, idling, and starting, requires additional dynamic driving characteristics beyond the conventional characteristics during durability driving tests. Hence, the relative positive acceleration (RPA) is further analyzed because RPA represents important dynamic characteristics to quantitatively evaluate both the frequency and magnitude of acceleration. Specifically, RPA is calculated by integrating the product of the vehicle speed $v(t)$ and the

instantaneous positive acceleration $a^+(t)$ over time, with normalization by the total trip distance X as follows [35]:

$$\text{RPA} = \frac{1}{X} \int_0^T v(t) \cdot a^+(t) dt. \quad (1)$$

Interestingly, the mean RPA and idling ratio are the highest in urban roads at 0.31 m/s² and 0.2955, decreasing in the order of rural to highway. These characteristics of EV operation suggest that vehicles operate under frequent and intense acceleration along with frequent idling in the type of urban road, whereas vehicles maintain a high speed with rare acceleration and idling in the type of highway road. Notably, the variances of all dynamic driving characteristics for EV #2, which are 34 times sparser than those of EV #1, are at least twice as large as the variances of EV #1, with the corresponding 95% CI at least 2.5 times wider. These differences would originate from the statistical principle that smaller sample sizes lead to greater variability [46]. Hence, these characteristics and variability should be considered in generating stochastic operational driving cycles for degradation experiments.

2.3 | Electrical Driving Characteristics of EVs

This subsection describes the electrical driving characteristics obtained from the actual durability driving tests of EV #1 (Figure 4a) and EV #2 (Figure 4b). Similar to the dynamic driving characteristics, notable differences are observed in the electrical driving characteristics depending on the road type (Figure 4 and Table 4). Specifically, the mean driving powers of the EVs based on the driving data are 10.13, 16.34, and 27.83 kW, and the mean

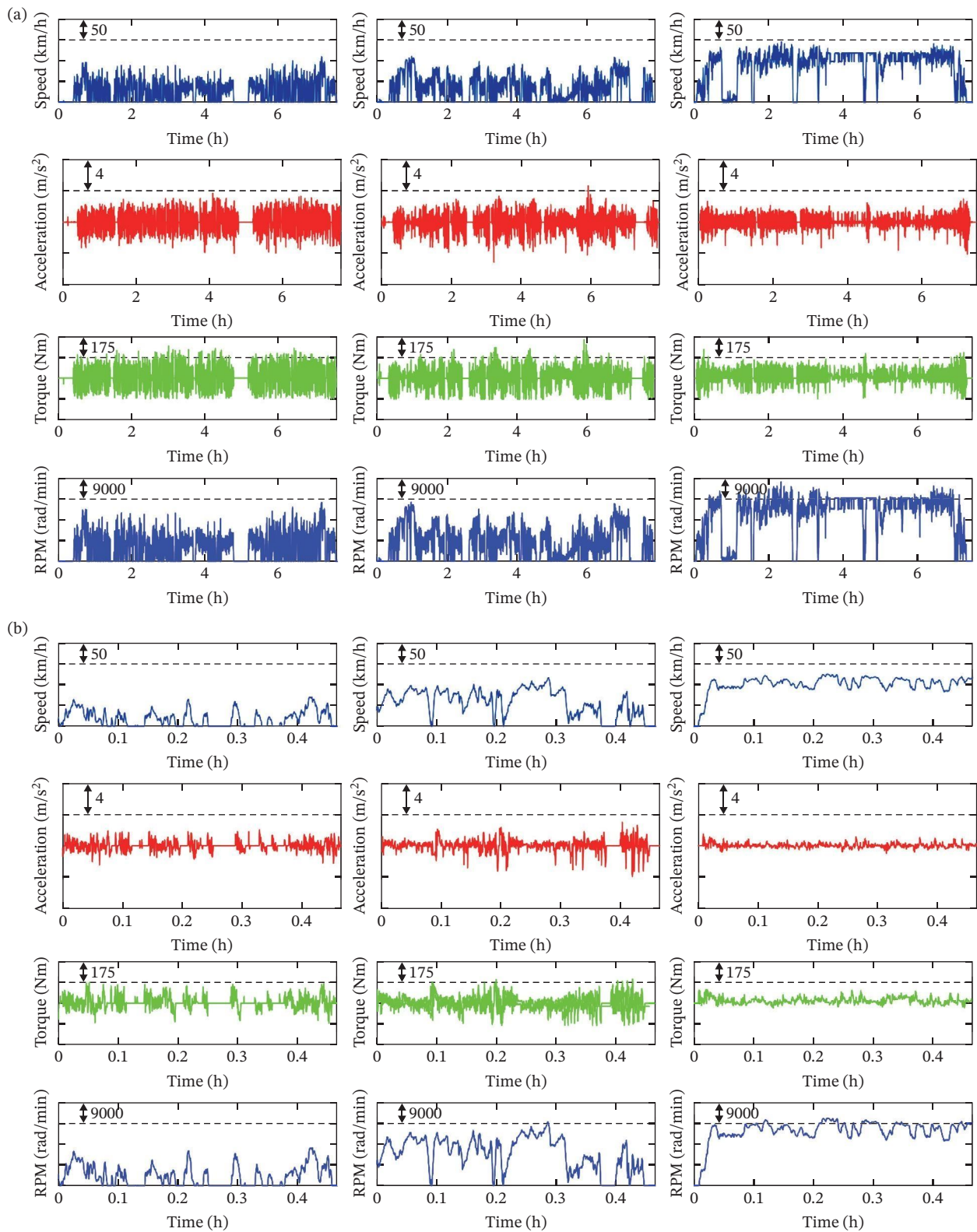


FIGURE 3 | Dynamic responses of urban, rural, and highway driving data for (a) EV #1 and (b) EV #2.

regenerative braking powers are 12.74, 14.86, and 17.62 kW in urban, rural, and highway road types, respectively. These differences in the electrical characteristics of the EVs suggest that both driving power consumption and regenerative braking power recovery increase as the mean speed increases from urban to rural and further on highway. Note that the 95% CI of the

mean driving power consumption across road types are separated by distances ranging from 2.51 to 7.33 kW for both EVs, thereby substantiating statistically distinct differences in the electrical driving characteristics across road types. Moreover, the mean driving current and the maximum driving current are the highest in the type of highway road at 47.31 and 262.14 A, confirming

TABLE 3 | Dynamic driving characteristics of actual durability driving tests and collected data volume.

Test vehicle	Road type	v_{avg} (km/h)	a_{avg} (m/s ²)	d_{avg} (m/s ²)	RPA_{avg} (m/s ²)	Idling ratio
EV #1	Urban	26.81 ± 1.30 [26.32, 27.42]	0.68 ± 0.04 [0.66, 0.69]	-0.60 ± 0.03 [-0.61, -0.59]	0.32 ± 0.02 [0.31, 0.33]	0.2457
EV #2		24.57 ± 8.46 [18.53, 30.63]	0.57 ± 0.13 [0.49, 0.68]	-0.56 ± 0.09 [-0.64, -0.50]	0.29 ± 0.07 [0.24, 0.34]	0.3452
EV #1	Rural	37.37 ± 2.86 [36.35, 38.77]	0.62 ± 0.06 [0.59, 0.65]	-0.58 ± 0.04 [-0.59, -0.56]	0.29 ± 0.03 [0.28, 0.30]	0.1418
EV #2		52.67 ± 15.91 [41.29, 64.06]	0.46 ± 0.12 [0.38, 0.54]	-0.48 ± 0.13 [-0.58, -0.40]	0.21 ± 0.06 [0.18, 0.25]	0.2256
EV #1	Highway	88.47 ± 4.14 [86.53, 90.79]	0.34 ± 0.04 [0.32, 0.36]	-0.33 ± 0.03 [-0.35, -0.31]	0.15 ± 0.02 [0.14, 0.16]	0.0373
EV #2		110.43 ± 14.31 [100.81, 120.04]	0.23 ± 0.08 [0.18, 0.28]	-0.22 ± 0.08 [-0.27, -0.17]	0.10 ± 0.04 [0.08, 0.13]	0.0919

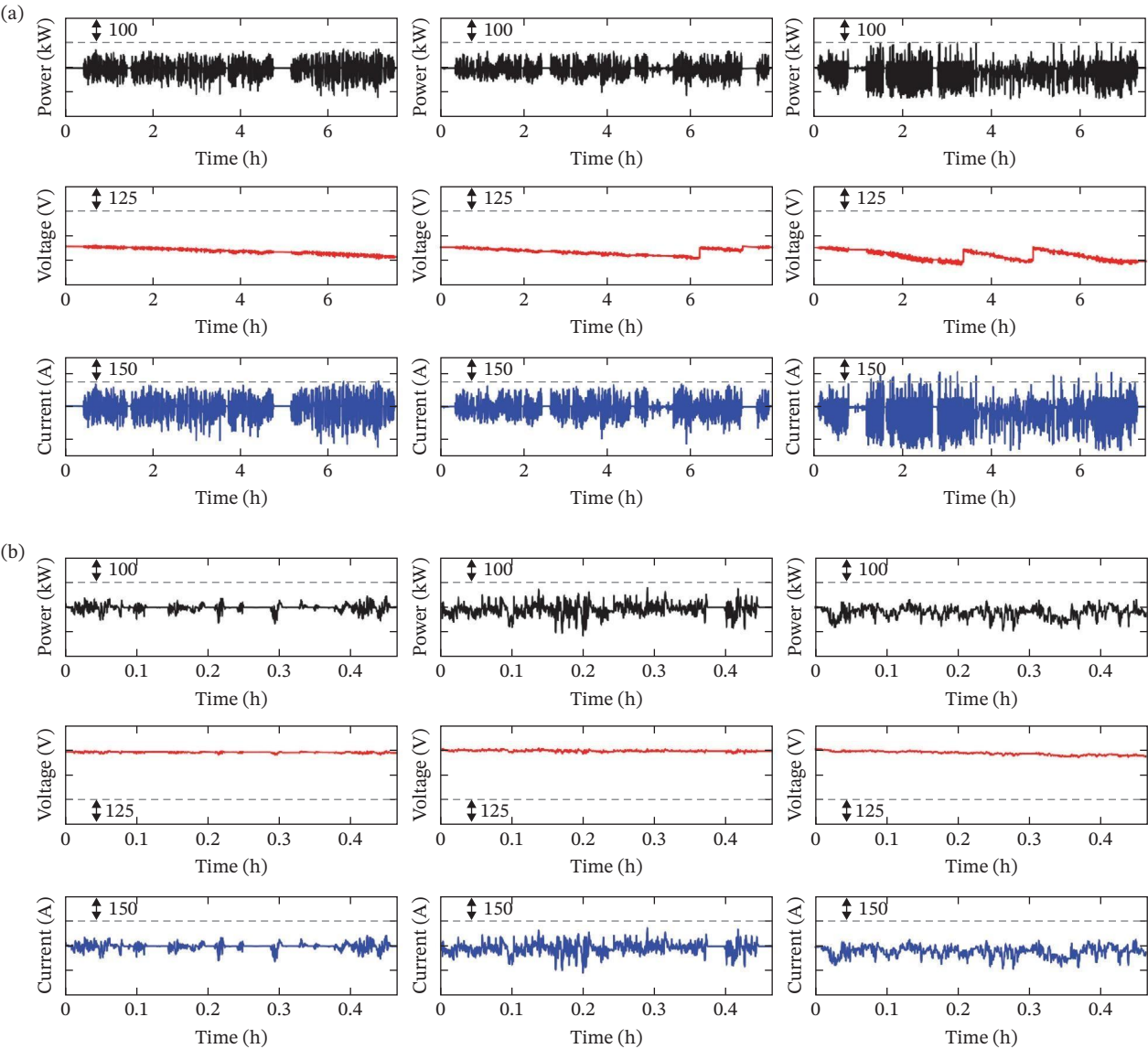


FIGURE 4 | Electrical responses of urban, rural, and highway driving data for (a) EV #1 and (b) EV #2.

TABLE 4 | Electrical driving characteristics of actual durability driving tests.

Test vehicle	Road type	$P_{\text{avg.driving}}$ (kW)	$P_{\text{avg.regenerative braking}}$ (kW)	$I_{\text{avg.driving}}$ (A)	$I_{\text{max.driving}}$ (A)
EV #1	Urban	10.50 ± 0.80 [10.16, 10.84]	12.91 ± 1.46 [12.29, 13.52]	20.16 ± 1.50 [19.53, 20.80]	262.44
EV #2		9.76 ± 2.70 [7.83, 11.69]	12.56 ± 2.34 [10.89, 14.24]	13.74 ± 3.93 [10.93, 16.55]	188.50
EV #1	Rural	14.74 ± 2.13 [13.84, 15.64]	14.45 ± 1.34 [13.88, 15.02]	28.67 ± 4.23 [26.89, 30.46]	264.75
EV #2		17.95 ± 5.24 [14.20, 21.70]	15.27 ± 3.91 [12.47, 18.07]	26.34 ± 7.56 [20.93, 31.75]	259.50
EV #1	Highway	24.29 ± 2.59 [22.96, 25.63]	17.27 ± 3.07 [15.67, 18.85]	48.14 ± 5.17 [45.48, 50.79]	267.90
EV #2		31.37 ± 7.34 [26.43, 36.30]	17.96 ± 4.88 [14.68, 21.24]	46.47 ± 12.51 [38.07, 54.87]	256.37

that the current increases with vehicle speed with a proportional relationship between power demand and speed. Notably, the mean regenerative braking power becomes relatively greater than the mean driving power from highway to rural and further on urban, with the regenerative braking power exceeding the driving power in the type of urban. This result confirms that deceleration occurs frequently in the type of urban and thereby driving characteristics, including stopping, idling, and starting, are more repeated in this environment, similar to the observations from the dynamic driving characteristic analysis. Hence, stochastic operational driving cycles for degradation experiments should account for these electrical driving characteristics to ensure the high fidelity of the stochastic driving scenarios.

2.4 | Charging Characteristics of EVs

This subsection describes the charging characteristics obtained from the actual durability driving test (Table 5). Note that this study analyzed the charging characteristics based on the charging measurements of EV #1. Charging is performed based on a static protocol, in contrast to the dynamic and variable characteristics of the driving process. The static characteristics of the charging protocol result in low sensitivity to vehicle variations, enabling the charging measurements obtained from a single vehicle to be considered sufficiently representative for the analysis. Hence, this study constructed detailed charging measurements for EV #1,

considering not only the representativeness of charging measurements from a single vehicle but also the substantial time, cost, and risk of data loss associated with conducting multiple field durability driving tests. The frequency of charging events differs by road types because of variations in daily battery consumption. Specifically, the daily charging frequency includes one postdriving charge (i.e., after driving) and zero or more mid-driving charges, each performed in the CC and constant-voltage (CCCV) mode at a C-rate of 1.5C. Hence, the mean battery consumptions are 54.6%, 70.6%, and 183.9% in urban, rural, and highway road types, respectively, with the corresponding charging event frequency observed to be no more than twice in urban and rural road types, whereas more than three times in the type of highway road. These differences in charging frequency suggest that vehicles operating in this type of highway require more than two mid-driving charging events because of the battery consumption exceeding 100%. This characteristic corresponds exactly to the electrical driving characteristics, in which power demand increases compared with those in urban and rural road types. Note also that mid-driving and postdriving charging differ in terms of the SOC range used between charges [47]. Hence, further analysis of the SOC at the start and end of charging is required to quantitatively compare the two charging patterns. Specifically, the mean SOC at the start of charging is 42.1% for mid-driving charging and 52.5% for postdriving charging, whereas the corresponding end of charging SOC is 87.4% and 97.8% for each charging for all road types. These

TABLE 5 | Charging characteristics of the actual durability driving test on EV #1.

Road type	Battery consumption (%)	Charging event frequency				Mid-driving charging		Postdriving charging	
		1	2	3	4	SOC _{start} (%)	SOC _{end} (%)	SOC _{start} (%)	SOC _{end} (%)
Urban	54.6 ± 4.3 [52.2, 57.0]	5	10	0	0	57.7 ± 10.3 [50.3, 65.1]	84.0 ± 5.8 [79.9, 88.1]	57.1 ± 11.9 [50.5, 63.7]	98.1 ± 2.5 [96.7, 99.5]
Rural	70.6 ± 3.8 [68.2, 73.0]	2	10	0	0	47.8 ± 9.6 [41.0, 54.6]	83.6 ± 5.1 [80.0, 87.2]	56.7 ± 15.0 [47.1, 66.2]	97.3 ± 3.1 [95.3, 99.2]
Highway	183.9 ± 5.6 [180.1, 187.7]	0	0	8	3	33.2 ± 5.7 [30.8, 35.6]	90.3 ± 7.1 [87.3, 93.3]	41.5 ± 17.2 [30.0, 53.1]	98.0 ± 2.3 [96.5, 99.5]
Total	98.1 ± 57.2	7	20	8	3	42.1 ± 13.0	87.4 ± 7.1	52.5 ± 15.9	97.8 ± 2.6

results suggest that mid-driving charging aims to secure the remaining driving range, whereas postdriving charging is performed primarily to fully charge the battery. Meanwhile, the 95% CIs of the SOC at the start and end of charging overlap across road types because the start and end of charging SOC are influenced by the driver's charging decision rather than by the road environment. Nevertheless, this study aims to design the degradation experimental process to replicate not only the driving characteristics but also the SOC range associated with the respective purposes of mid-driving and postdriving charging as well as the driver's charging pattern. Hence, these charging characteristics should be considered in designing the degradation experimental process to replicate actual operational conditions with a high level of fidelity.

3 | The Proposed Framework

This study establishes the scenario for stochastic degradation experiments by analyzing the driving characteristics of the EV of interest, as described in Section 2. The operational profile required for the discharging process is also generated in the degradation experiments. This framework aims to design stochastic degradation experiments for LIBs in EVs (Figure 5).

A detailed scenario is established to account for three considerations. First, a detailed pattern of the degradation experiment is constructed based on the analysis of both the mid-driving and postdriving charging characteristics. Second, the SOC range corresponding to each charging process is determined from the statistical analysis of actual charging data, leading to the calculation

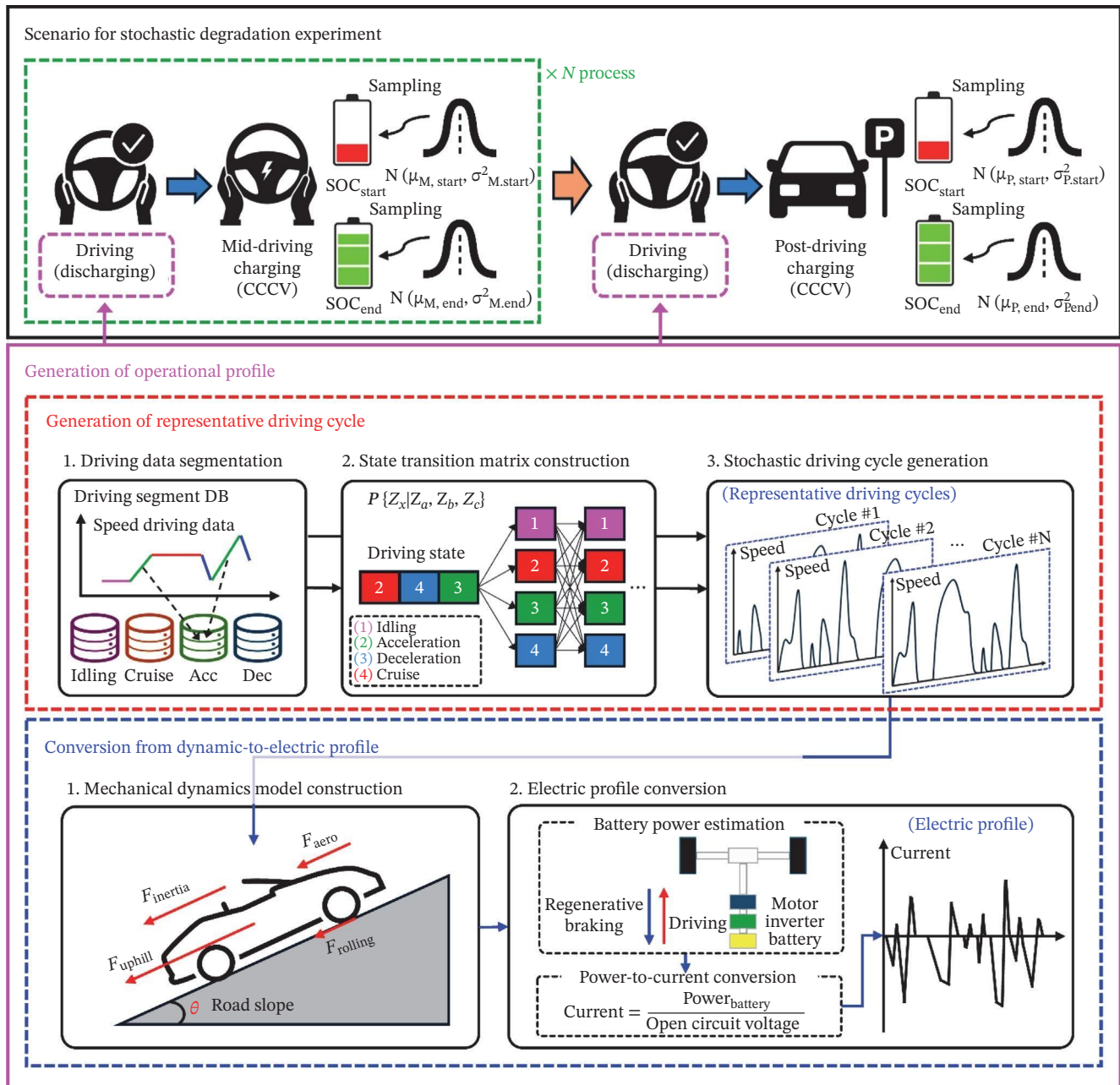


FIGURE 5 | Graphical illustration of the proposed framework.

of the repetition number of the discharging profile. Third, the operational profiles required for each charging and discharging process are generated based on the driving data corresponding to the actual durability driving test. The proposed scenario contributes to representing the stochastic driving characteristics observed in actual durability driving tests and thereby replicates the daily test procedures for the EV of interest.

The operational profile required for the discharging process of the degradation experiment was further generated to reflect the stochastic driving characteristics. The detailed generation of operational profiles (the pink box in Figure 5) comprises two phases, including the generation of a representative driving cycle and conversion from a dynamic-to-electric profile. The first phase stochastically generates representative driving cycles using the database for the driving segment, state transition matrix, and four-generation rules. This phase aims to model the stochastic driving characteristics of the EV of interest (the red dashed box in Figure 5). The second phase converts the representative driving cycle into an electric profile by addressing a mechanical dynamics model and electric characteristics of the LIBs deployed, including power efficiency and OCV (the blue dashed box in Figure 5). This method serves to generate the operational profile that reflects the dynamic driving characteristics and variability caused by uncontrollable factors and converts the electric profile suitable for degradation experiments.

3.1 | Scenario for Stochastic Degradation Experiment

This subsection outlines a detailed generation method of the scenario for stochastic degradation experiments in the proposed framework. First, the detailed pattern of the degradation experiment is constructed by analyzing the dominant charging patterns observed in each road type (Figure 6). Specifically, the pattern of degradation experiment begins with the discharging process, followed by dominant charging patterns, including mid-driving charging and postdriving charging situations because of daily battery consumption. Note that the number of mid-driving charges varies by road type because of differences in the dominant charging event frequency, as analyzed in Table 5. Hence, the charging pattern of the degradation experiment is determined as one mid-driving charge followed by a postdriving charge for urban and rural road types, whereas two mid-driving charges are followed by a postdriving charge for the type of highway road. Note that the rest process is considered to reflect the standby situation following the completion of postdriving charging.

Second, the SOC range corresponding to each charging process in the degradation experiments is determined based on the normal

distribution assumption [48] and the statistical parameters derived from the actual charging data, as follows:

$$\begin{aligned} \text{SOC}_{i,\text{start}} &\sim N(\mu_{i,\text{start}}, \sigma_{i,\text{start}}^2) \\ \text{and } \text{SOC}_{i,\text{end}} &\sim N(\mu_{i,\text{end}}, \sigma_{i,\text{end}}^2), i \in \{M, P\}, \end{aligned} \quad (2)$$

where $\text{SOC}_{*,\text{start}}$, $\text{SOC}_{*,\text{end}}$, $N(\mu_*, \sigma_*^2)$, M , and P denote the value of start SOC, the value of end SOC, the normal distribution with mean μ_* and variance σ_*^2 , the symbol of mid-driving charging, and the symbol of postdriving charging, respectively. The values of the start and end SOC $\text{SOC}_{i,\text{start}}$ and $\text{SOC}_{i,\text{end}}$ are sampled from driving data of field experiments. Specifically, the normal distribution corresponding to mid-driving charging and postdriving charging is used to determine the SOC range for each charging process. Note that the SOC ranges were sampled for each charging process based on the statistical parameters corresponding to each road type in Table 5. Note that this decision might replicate the stochastic variability of the SOC range in the charging characteristics of the EV of interest. Then, the repetition number of the discharging profile is calculated based on the predetermined SOC range, as follows:

$$N_{\text{rep}} = \left\lceil \frac{\text{SOC}_{\text{end}}^{\text{previous}} - \text{SOC}_{\text{start}}^{\text{current}}}{\Delta \text{SOC}_{\text{discharging}}} \right\rceil, \quad (3)$$

where N_{rep} , $\text{SOC}_{\text{end}}^{\text{previous}}$, $\text{SOC}_{\text{start}}^{\text{current}}$, $\Delta \text{SOC}_{\text{discharging}}$, and $\lceil \cdot \rceil$ denote the repetition number, the end SOC of the previous charging process, the start SOC of the current charging process, the reduction of SOC per discharging profile, and the ceiling function, respectively. The repetition number N_{rep} is calculated by applying the ceiling function to the division of SOC range for each discharging process $\text{SOC}_{\text{end}}^{\text{previous}} - \text{SOC}_{\text{start}}^{\text{current}}$ by the reduction of SOC per discharging profile $\Delta \text{SOC}_{\text{discharging}}$.

Third, the operational profiles required for each charging and discharging process are generated by considering both charging and driving characteristics of the EV of interest. Note that the charging process is executed under the same charging mode, whereas the discharging process is examined under the stochastic driving mode in the actual durability driving test. Hence, this study further generates the operational profiles required for the discharging process in the degradation experiments to reflect the variability in driving characteristics caused by uncontrollable factors. The detailed process for the generation of operational profile is described in the following subsection.

3.2 | Generation of Operational Profile

This subsection outlines the generation of the operational profile required for the discharging process in the degradation

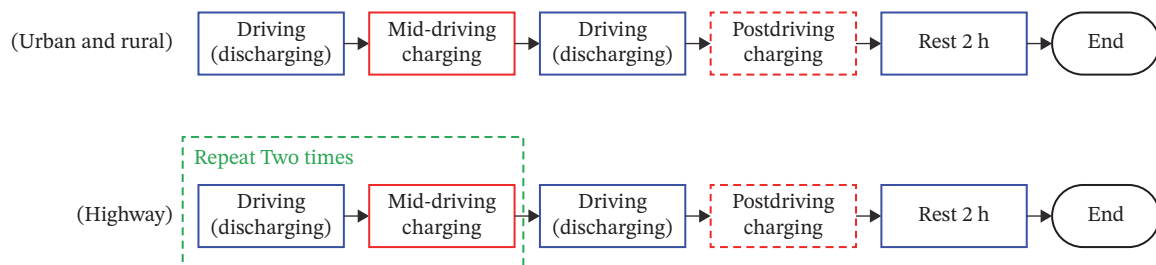


FIGURE 6 | Detailed pattern of degradation experiment corresponds to each road type.

experiments (the pink box in Figure 5). The detailed process for generation of operational profile comprises two phases, including generation of representative driving cycle and conversion from dynamic-to-electric profile. The first phase encompasses three major steps: driving data segmentation, state transition matrix construction, and stochastic driving cycle generation (the red dashed box in Figure 5). First, driving data are segmented depending on road types by analyzing the dynamic characteristics of field measurements. Specifically, the driving data are interpolated into 1-s intervals to address sampling differences in the collected data (the vertical dashed line in Figure 7a). Subsequently, these data are classified into driving states at each time step (dot in Figure 7a) based on the definitions of the WLTC [35], as follows:

$$\begin{aligned} \text{Idling} &: v(t) < 5 \text{ km/h}, -0.139 \text{ m/s}^2 \leq a(t) \leq 0.139 \text{ m/s}^2 \\ \text{Cruise} &: v(t) \geq 5 \text{ km/h}, -0.139 \text{ m/s}^2 \leq a(t) \leq 0.139 \text{ m/s}^2 \\ \text{Acceleration} &: a(t) > 0.139 \text{ m/s}^2 \\ \text{Deceleration} &: a(t) < -0.139 \text{ m/s}^2 \end{aligned} \quad (4)$$

where $v(t)$ and $a(t)$ denote the instantaneous speed and acceleration at time t . Note that driving data are classified into four states of idling, cruise, acceleration, and deceleration based on speed and acceleration thresholds of 5 km/h and $\pm 0.139 \text{ m/s}^2$. These classified data are combined with consecutive driving states to form segmented data (the purple, red, green, and blue

lines in Figure 7a). In other words, each driving segment is continued until the driving state changes, resulting in varying segment lengths. The driving states of rapid acceleration and rapid deceleration are also defined (Figure 7b) by considering the characteristics of the highway as follows:

$$\begin{aligned} \text{Rapid acceleration} &: (v(t) < \bar{v}) \cap (t_{\text{start}} \leq t \leq t_{\bar{v}, \text{init}}) \cap (\bar{v} \geq 80 \text{ km/h}) \\ \text{Rapid deceleration} &: (v(t) < \bar{v}) \cap (t_{\bar{v}, \text{final}} \leq t \leq t_{\text{end}}) \cap (\bar{v} \geq 80 \text{ km/h}) \end{aligned} \quad (5)$$

where $\bar{v}$, t_{start} , $t_{\bar{v}, \text{init}}$, $t_{\bar{v}, \text{final}}$, and t_{end} denote the mean speed of a driving period (the red dashed line in Figure 7b), the time when the vehicle starts moving from the idling state, the time when $\bar{v}$ is first reached, the time when $\bar{v}$ is last reached, and the time just before the vehicle returns to the idling state, respectively. The state titled rapid acceleration is defined as the period from the idling state to just before reaching the mean speed in a driving period, whereas the state titled rapid deceleration is defined as the period from the last mean speed to just before reaching the idling state. These states are defined to classify significant increases and decreases in speed during driving. Note that rapid acceleration and deceleration segments include multiple driving states, such as cruise, acceleration, and deceleration. Note also that rapid acceleration and deceleration are used only to define the beginning and end of the highway driving cycle. In this manner, driving segments under urban and rural road types are used to construct four databases (idling DB, cruise DB, acceleration DB, and deceleration DB), including the speed data with matching acceleration, torque, and RPM data (Figure 7a). Driving segments under the type of highway road are used to construct five databases (cruise DB, acceleration DB, deceleration DB, rapid acceleration DB, and rapid deceleration DB). Note that the idling database is not constructed for the type of highway road because the idling state is not observed in this operational condition.

Second, the state transition matrix is constructed depending on road types using the driving segment database. Specifically, this study calculates the state transition probabilities between four driving segments based on a third-order Markov process, which are defined as follows:

$$\begin{aligned} p_{(x,abc)} &= P\{Z_x | Z_a, Z_b, Z_c\} \\ &= \frac{N_{(x,abc)}}{N_{(\text{idling},abc)} + N_{(\text{cruise},abc)} + N_{(\text{acc},abc)} + N_{(\text{dec},abc)}}, \end{aligned} \quad (6)$$

$$Z \in \{\text{idling, cruise, acceleration (acc), deceleration (dec)}\},$$

where p_* , N_* , and Z_* denote the transition probability, the number of transition case, and the driving state, respectively. Specifically, the $p_{(x,abc)}$ represents the probability of the next driving state, given Z_a (the previous driving state), Z_b (the second previous driving state), and Z_c (the third previous driving state), which is calculated as the ratio of occurrences of the specific driving state to all possible occurrences of the previous three driving states. This Markov process models driving patterns by empirically estimating transition probabilities between discrete states in observed systems [49] considering the correlations among three consecutive driving states. Note that this process aims to capture the variability and continuity of the actual driving patterns. Hence, the state transition matrix is constructed based on transitions among the four driving states as follows:

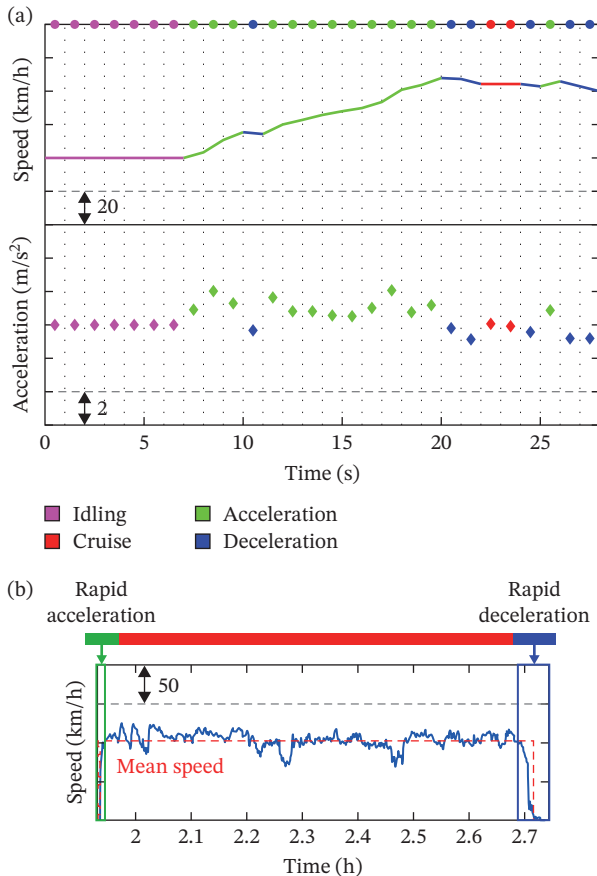


FIGURE 7 | Driving data segmentation for (a) urban and rural and (b) highway.

$$P = \begin{bmatrix} p_{(1,111)} & p_{(2,111)} & p_{(3,111)} & p_{(4,111)} \\ \vdots & \vdots & \vdots & \vdots \\ p_{(1,312)} & p_{(2,312)} & p_{(3,312)} & p_{(4,312)} \\ p_{(1,313)} & p_{(2,313)} & p_{(3,313)} & p_{(4,313)} \\ p_{(1,314)} & p_{(2,314)} & p_{(3,314)} & p_{(4,314)} \\ \vdots & \vdots & \vdots & \vdots \\ p_{(1,421)} & p_{(2,421)} & p_{(3,421)} & p_{(4,421)} \end{bmatrix}. \quad (7)$$

$f1 = \text{idling}, 2 = \text{cruise}, 3 = \text{acc}, 4 = \text{dec}.$

Each row of the state transition matrix represents the probabilities of transitioning from the given three previous driving states to the current driving state, where the sum of each row equals 1. Once the previous driving states are determined, the state transition matrix can be employed to probabilistically select the current state.

Third, a representative driving cycle is stochastically generated for each road type through a defined order of three processes: (1) determining the state using a state transition matrix, (2) selecting the driving segment based on four rules, and (3) optimizing the dynamic driving characteristics employing BO (Figure 8). In the process (1-i), the driving cycle on urban and rural road types begins with idling and acceleration driving states to replicate actual operational conditions, considering that a vehicle starts

moving from a stop. The next driving state is selected based on a second-order Markov process ($p_{\text{initial}} = p\{Z_x | \text{acc, idling}\}$) because only two driving states are predetermined. In process (1-ii), the driving cycle on highways is predefined with rapid acceleration and deceleration driving states to better reflect actual operational conditions. In process (1-iii), the subsequent driving states are repeatedly generated by selecting the driving state corresponding to the three previous driving states based on the state transition matrix in Equation (7). Note that the driving state following rapid acceleration in the type of highway road is determined based on the last three states in the rapid acceleration segment, considering that the rapid acceleration driving segment encompasses multiple driving states (cruise, acceleration, and deceleration). In process (2), a specific segment corresponding to the selected state is determined in the consideration of four rules, as follows:

Speed continuity rule: $|v_a(\text{end}) - v_x(0)| \leq v_{\text{threshold}}$.

Stop rule: $Z = \text{idling if } (Z_a = \text{dec}) \cap (v_a(\text{end}) - 0 \leq v_{\text{threshold}})$.

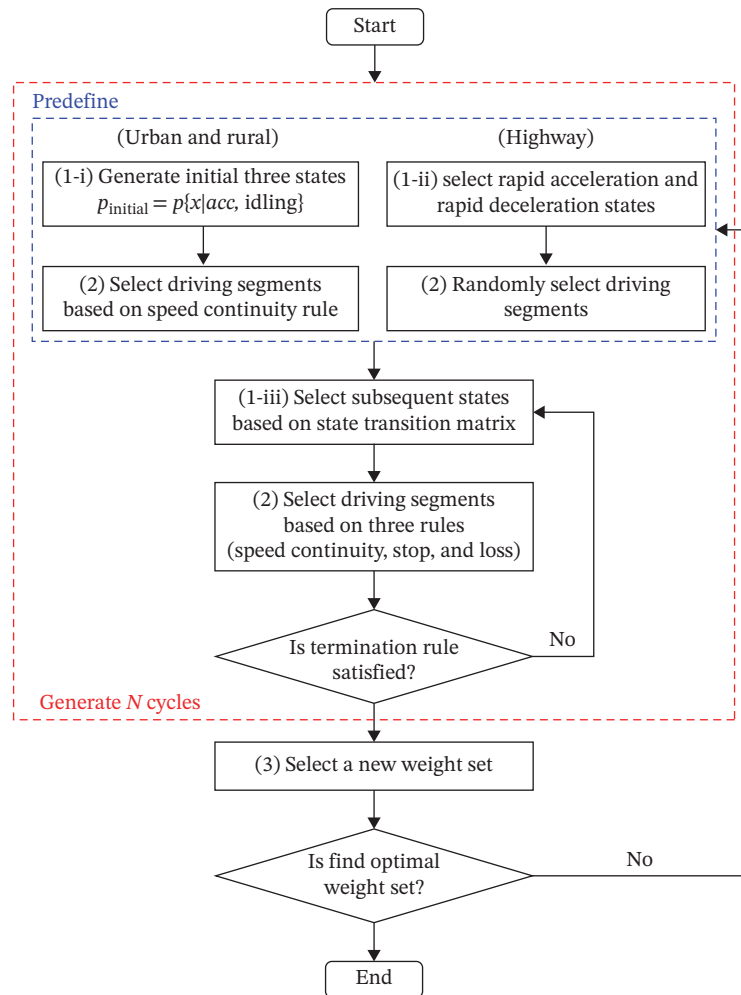


FIGURE 8 | Flowchart of the stochastic driving cycle generation.

$$\begin{aligned}
 &\text{Loss rule: } \operatorname{argmin} \left(\sum_i w_i \left| \frac{\hat{\theta}_i - \theta_i}{\theta_i} \right| \right), \\
 &i \in \{r_{\text{idling}}\} \text{ in idling state} \\
 &i \in \{v_{\text{avg}}, v_{\text{std}}, \text{RPA}, r_{\text{cruise}}, r_{\text{acc}}, r_{\text{dec}}\} \text{ in cruise state} \\
 &i \in \{v_{\text{avg}}, v_{\text{std}}, a_{\text{avg}}^+, \text{RPA}, r_{\text{cruise}}, r_{\text{acc}}, r_{\text{dec}}\} \text{ in acceleration state} \\
 &i \in \{v_{\text{avg}}, v_{\text{std}}, a_{\text{avg}}^-, \text{RPA}, r_{\text{cruise}}, r_{\text{acc}}, r_{\text{dec}}\} \text{ in deceleration state}
 \end{aligned} \quad (8)$$

$$\begin{aligned}
 &\text{Termination rule: } (l_{\text{threshold, lower}} \leq l \leq l_{\text{threshold, upper}}) \\
 &\cap (|v_a(\text{end}) - v_{\text{refer}}| \leq v_{\text{threshold}}),
 \end{aligned}$$

where w_i , $\hat{\theta}_i$, θ_i , r_* , and l denote the weight for each characteristic, the dynamic driving characteristic parameter of the accumulatively generated driving cycle, the dynamic driving characteristic parameter of the driving data, the ratio of driving states, and the generation length, respectively. Note that the speed continuity rule enhances continuity by constraining the speed difference between the currently generated driving cycle and the current driving segment. $|v_a(\text{end}) - v_x(0)|$ quantifies the difference between the final speed of the generated cycle and the initial speed of the current segment. The stop rule transitions the current state to idling when the previous state is deceleration and the final generated speed is below the speed threshold. This rule is addressed to replicate stop situations, such as signal stops and traffic jams. The loss rule is a constraint that minimizes the difference between dynamic driving characteristics of the currently generated driving cycle and actual driving data. Loss is calculated as the weighted sum of the relative errors of individual characteristics between the generated cycle and actual driving data. Note that dynamic driving characteristics are considered the most representative indicators for each driving state. The termination rule terminates the driving cycle generation based on the speed threshold and generated length condition. Length thresholds are defined as $l_{\text{WLTC}} \cdot \frac{\mu \pm \sigma}{\mu}$, based on the WLTC standard generation length and statistical variation of actual driving data [35]. Note that the reference speed on urban and rural road types is defined as zero, whereas reference speed on highways is defined as initial speed in the rapid deceleration segment. Hence, the proposed generation method selects the driving segment that optimally satisfies the three rules (speed continuity rule, stop rule, and loss rule) and terminates the driving cycle generation when the termination rule is satisfied. Note also that driving segments in the predefined state for urban and rural road types follow only the speed continuity rule, whereas those on the highway road type are randomly selected. In process (3), the weight optimization process finds the optimal weight based on BO. This process aims to optimize the importance of each dynamic driving characteristic. BO can effectively find global optimal solutions by iteratively constructing the posterior distribution through fitting a Gaussian process to the given data points and selecting a new hyperparameter space for subsequent iterations [50]. Note that BO has the advantage of weight optimization by addressing limitations of metaheuristic optimization algorithms, including cuckoo search algorithm (CSO) and grey wolf optimization (GWO) in terms of convergence performance and speed for complex problems [51]. Metaheuristic optimization algorithms search for optimal solutions through trial-and-error strategies based on diversification and intensification, thereby having limitations in convergence performance and speed for high-

dimensional problems [52]. In contrast, BO iteratively explores and exploits the parameter space by constructing a probabilistic surrogate model of the objective function, thereby focusing evaluations on regions exhibiting the greatest potential for improvement. The detailed theory and pseudo-code of the BO are provided in Appendix B (Algorithm A1). The objective function of BO is as follows:

$$\begin{aligned}
 &W^* = \operatorname{argmax}\{-f(W)\}, \\
 &f(W) = \operatorname{mean} \left(\frac{1}{N} \sum_{j=1}^N \left| \frac{\hat{\theta}_i^j(w_i) - \theta_i}{\hat{\theta}_i^j(w_i)} \right| \right) + \operatorname{var} \left(\frac{1}{N} \sum_{j=1}^N \left| \frac{\hat{\theta}_i^j(w_i) - \theta_i}{\hat{\theta}_i^j(w_i)} \right| \right), \\
 &i \in \{v_{\text{avg}}, v_{\text{std}}, a_{\text{avg}}^+, a_{\text{avg}}^-, \text{RPA}, r_{\text{idling}}, r_{\text{cruise}}, r_{\text{acc}}, r_{\text{dec}}\} \text{ for urban, rural} \\
 &i \in \{v_{\text{avg}}, v_{\text{std}}, a_{\text{avg}}^+, a_{\text{avg}}^-, \text{RPA}, r_{\text{cruise}}, r_{\text{acc}}, r_{\text{dec}}\} \text{ for highway}
 \end{aligned} \quad (9)$$

where W^* , N , and $\hat{\theta}_i^j(w_i)$ denote the optimal weight set, the total number of generated driving cycles in each iteration, and the i th dynamic driving characteristic of the j th generated driving cycle,

respectively. The term $\frac{1}{N} \sum_{j=1}^N \left| \frac{\hat{\theta}_i^j(w_i) - \theta_i}{\hat{\theta}_i^j(w_i)} \right|$ represents the mean relative error of a specific dynamic driving characteristic over N generated cycles, quantitatively evaluating the representativeness of the generated cycles compared to actual driving data. Note that the objective function in urban and rural road types is calculated based on the relative errors of eight dynamic driving characteristics, whereas the objective function in the type of highway road is calculated based on the relative errors of seven dynamic driving characteristics, excluding the idling ratio.

The second phase entails two major steps: the construction of the mechanical dynamics model and conversion to the electric profile (the blue dashed box in Figure 5).

First, a mechanical dynamics model is constructed in consideration of the mechanical characteristics of EVs. Specifically, this study employed dynamic characteristics of EVs to estimate the required power based on dynamic measurements, such as speed and acceleration, as follows [43]:

$$P_m(t) = T_m(t) \cdot \left(\frac{2\pi}{60} \cdot \text{RPM}(t) \right), \quad (10)$$

where $P_m(t)$, $T_m(t)$, and $\text{RPM}(t)$ denote the required motor power, the estimated motor torque, and the RPM, respectively. The value of $\text{RPM}(t)$ corresponds to each driving segment of the generated driving cycle, and the estimated motor torque $T_m(t)$ is derived from the sum of four forces based on the force balance principle as follows:

$$\begin{aligned}
 T_m(t) = & \operatorname{gr} \cdot R \cdot \left(\frac{1}{2} \rho_{\text{air}} A_f C_D v^2(t) + m a(t) + \mu m g \cdot \cos(\theta(t)) \right. \\
 & \left. + m g \cdot \sin(\theta(t)) \right),
 \end{aligned} \quad (11)$$

where F_* , g , ρ_{air} , and $\theta(t)$ denote the driving force, the rolling resistance coefficient, the gravitational acceleration, the air density, and the road slope, respectively. In addition, gr , R , m , A_f , C_D are the vehicle specific parameters, representing the gear ratio, the wheel radius, the vehicle mass, the frontal area, and the air drag coefficient, respectively. Specifically, the motor torque $T_m(t)$ is estimated by considering four forces acting on the EV of

interest: aerodynamic drag force $\frac{1}{2}\rho_{\text{air}}A_fC_Dv^2(t)$, inertial force $ma(t)$, rolling resistance force $\mu mg \cdot \cos(\theta(t))$, and uphill driving force $mg \cdot \sin(\theta(t))$. The aerodynamic drag and inertial forces are calculated with speed $v^2(t)$ and acceleration $a(t)$ from driving segments, and rolling resistance and uphill driving forces are calculated with road slope $\theta(t)$ as follows:

$$\theta(t) = \sin^{-1} \left(\frac{1}{\sqrt{1 + \mu^2}} \cdot \frac{1}{mg} \cdot \left(\frac{gr}{R} \cdot \hat{T}_m - ma(t) - \frac{1}{2}\rho_{\text{air}}A_fC_Dv^2(t) \right) \right) - \tan^{-1}(\mu) \quad (12)$$

where $\hat{T}_m$ denotes the motor torque obtained from the driving data. The required motor torque $T_m(t)$ is estimated from Equation (11) based on the speed, acceleration, and road slope of the generated driving cycle. Note that the proposed method contributes to reflected torque differences due to acceleration changes at the connection points between segments during the driving cycle generation process. Hence, the proposed model estimates the required profile for motor power to drive the generated driving cycle.

Second, the profile for motor power is converted into an electric profile for degradation experiments by considering the electric characteristics of the EV system of interest, including the power efficiency between the motor and the LIB pack and OCV data. Specifically, the electric profile is converted based on the required LIB pack power and OCV as follows:

$$I_b(t) = \frac{P_b(t)}{\text{OCV}(\text{SOC}(t))}, \quad (13)$$

where $I_b(t)$, $P_b(t)$, OCV, and $\text{SOC}(t)$ denote the converted LIB pack current, the required LIB pack power, the OCV, and the SOC, respectively. The required LIB pack power originates from the required motor power depending on the power flow direction as follows:

$$P_b(t) = \begin{cases} -P_m(t) \cdot \eta, & \text{if } P_m(t) \geq 0 \\ -P_m(t) \cdot \frac{1}{\eta}, & \text{if } P_m(t) < 0 \end{cases} \quad (14)$$

where η denotes the power efficiency from the LIB pack to the motor during driving. The required LIB pack power is calculated as the negative product of power efficiency when $P_m(t) \geq 0$ (regenerative braking), and as the negative product of the reciprocal of the power efficiency when $P_m(t) < 0$ (driving) [43]. Note that this conversion accounts not only for the power flow between the motor and the LIB pack during regenerative braking and driving but also for the reversal of signs due to the relationship between power supply and consumption. The OCV is determined by matching the input SOC to the corresponding value on the OCV-SOC curve (Figure 1). Specifically, the SOC is derived from the power consumption using the Coulomb-counting method as follows [43]:

$$\text{SOC}(t) = \text{SOC}_0 - \int \frac{P_b(t)}{3600 \cdot E_b} dt, \quad (15)$$

where SOC_0 and E_b denote the initial SOC and the power-rated capacity. The SOC is calculated starting from the predefined

initial SOC SOC_0 by accumulating the required LIB pack power at each time step relative to the power-rated capacity $\frac{P_b(t)}{3600 \cdot E_b}$. Hence, the electric profile is obtained by converting the required motor power into the required LIB pack power considering the power efficiency according to the power sign and then finally dividing it by the OCV corresponding to the calculated SOC.

4 | Results and Discussion

This section comprehensively analyzes the proposed framework for designing stochastic degradation experiments for LIBs in EVs. First, the operational profile required for the discharging process was generated through a sequential implementation procedure. Second, the fitness of the proposed method for generating an operational profile is evaluated by comparing the dynamic characteristics of the generated driving cycles with the actual driving data. This subsection also validates the effectiveness of optimal weights using the BO. Third, the fidelity of the proposed method for generating an operational profile is evaluated by comparing the energy consumption of the converted electric profile required for the discharging process with the actual driving data. In addition, this subsection validates the effectiveness of the estimated road slope in calculating the required LIB pack power corresponding to the generated driving cycles. Fourth, the superiority of the proposed framework is discussed based on the implementation results of the stochastic degradation experiments compared with the actual durability driving tests.

4.1 | Generation of Operational Profile

This subsection shows the detailed generation results of the operational profile. The operational profile corresponding to the randomly selected road type is generated through two phases.

First, the representative driving cycle is generated by encompassing three steps (the red boxes in Figure 9). In the first step, the driving data are segmented into four driving states (idling, cruise, acceleration, and deceleration) with the speed and acceleration thresholds of 5 km/h and $\pm 0.139 \text{ m/s}^2$. Note that this approach ensures the robustness of driving-state segmentation independent of the characteristics of driving measurements. Previous studies mainly employed data-driven clustering methods, including k -means and spectral clustering algorithms, with the limitation of high sensitivity to the characteristics of measurements [40, 53]. Note that these clustering approaches need to optimize the number of clusters to identify the representative driving states of measurements, exhibiting a high dependency on measurements. The proposed method addresses these limitations by defining driving states based on specific thresholds, enabling consistent driving state segmentation across diverse driving measurements. The idling ratio decreases from 34.52% to zero for EV #1 and from 28.57% to zero for EV #2, whereas the cruise ratio increases from 9.79% to 41.36% for EV #1 and from 10.45% to 52.97% for EV #2 in that the road type transitions from urban to highway. The specific ratios of each driving state are illustrated in Figure 10. This observation indicates that stopping occurs more frequently in urban and rural road types due to the influence of speed limits and traffic signals, highlighting the importance of generating a representative driving cycle that accurately reflects the dynamic driving characteristics of each road type. The second

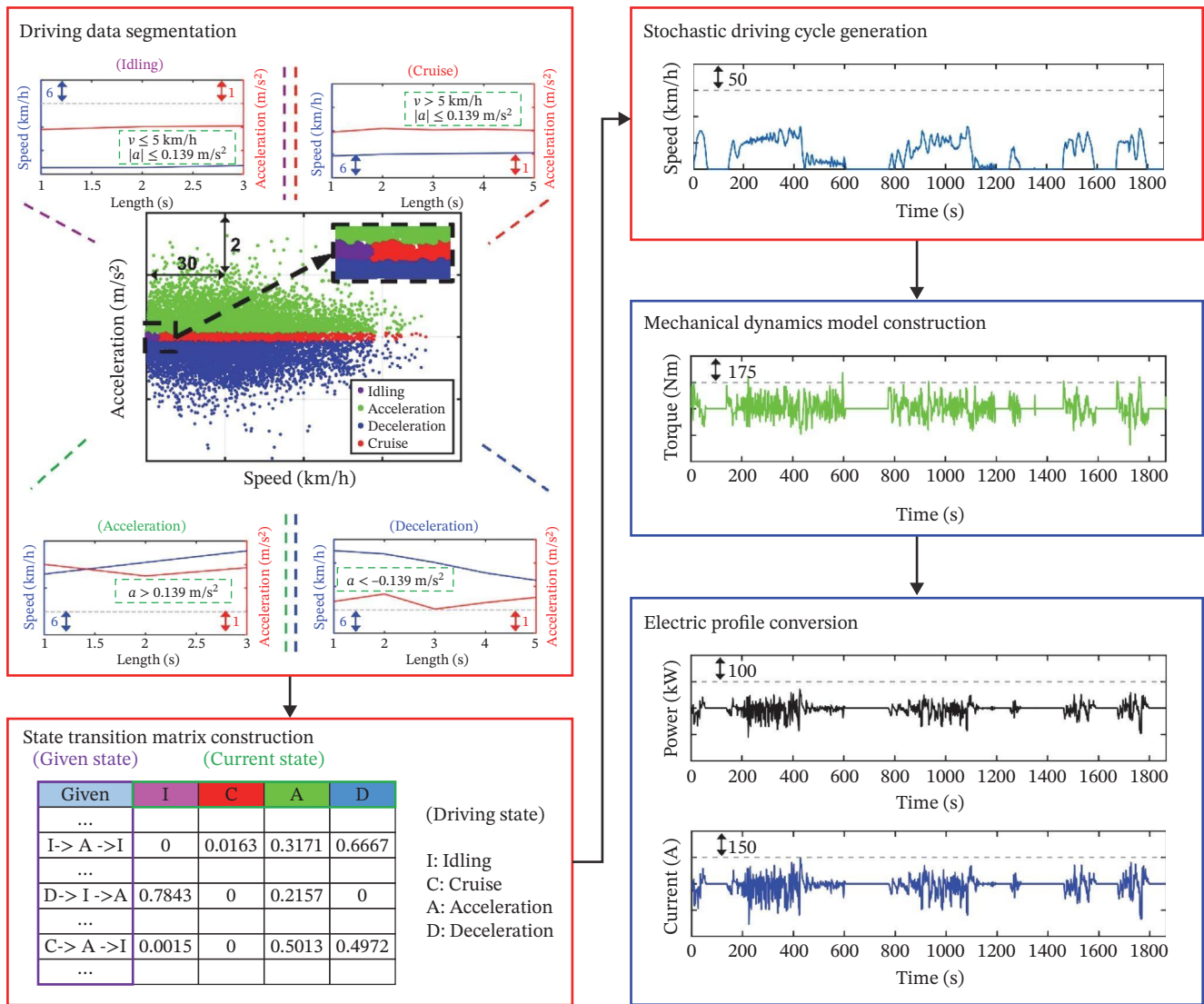


FIGURE 9 | Phase-wise implementation of the generation of operational profile.

step constructs a state transition matrix to represent the transitions between four driving states: idling, acceleration, deceleration, and cruise. The transition probabilities of driving states in sequential driving segments were quantitatively calculated using a third-order Markov process. Hence, driving patterns could be modeled for each road type using the actual driving data. Figure 11 shows the state transition matrix, illustrating the transition patterns among different driving states. The total number of possible scenarios amounts to 256 ($4 \times 4 \times 4 \times 4$), considering four driving states (idling, cruise, acceleration, and deceleration) in the state transition matrices for urban and rural road types. However, the number of valid scenarios is reduced to 108 ($4 \times 3 \times 3 \times 3$) because consecutive repetition of the same driving state is not allowed. Note that the number of valid scenarios is further reduced to 24 ($3 \times 2 \times 2 \times 2$) for highway road type, considering only three driving states (cruise, acceleration, and deceleration). This work can be explained by the fact that transitions to the cruise state occur more frequently on the type of highway road than in urban and rural road types, indicating that a more stable driving pattern is maintained on highways. In the third step, a representative driving cycle is generated using a stochastic driving cycle generation method. This generation method aims to

represent actual driving data by considering four rules: speed continuity, signal stop, loss minimization, and termination. Figure 12 illustrates the detailed process of generating the representative driving cycle. First, the next driving state is determined based on the state transition matrix (Figure 12(1)). Second, the candidate driving segments corresponding to the determined driving state are evaluated based on three rules: speed continuity rule, stop rule, and loss rule (Figure 12(2)). Third, the most optimal driving segment that satisfies all three rules is selected (Figure 12(3)). Fourth, the next driving state is determined based on the state transition matrix with the updated driving state (Figure 12(4)). By repeating these four processes until the termination rule was satisfied, the representative driving cycle can be stochastically generated.

Second, the generated representative driving cycle is converted into an electric profile encompassing two steps (the blue boxes in Figure 9). In the first step, the required motor torque and power are estimated to drive the generated representative driving cycle using the mechanical dynamics model. This model is designed to estimate the required motor torque and power based on four driving forces with dynamic measurements, including speed,

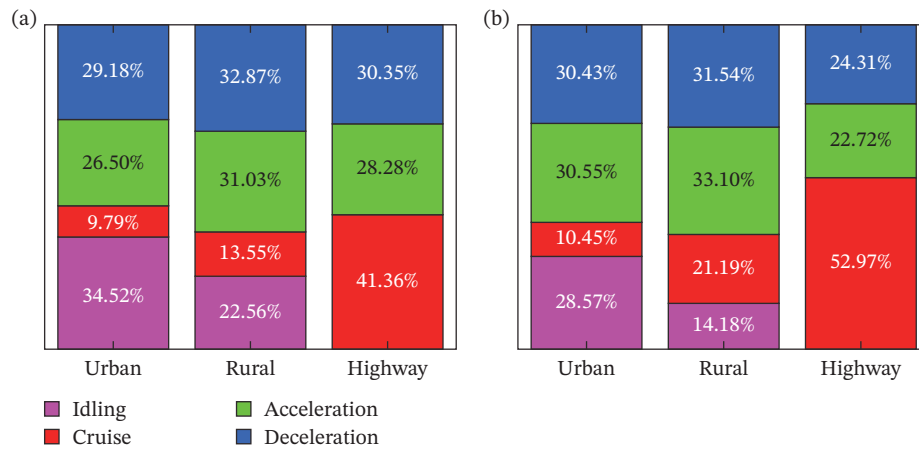


FIGURE 10 | Ratio of driving states for different road types: driving data for (a) EV #1 and (b) EV #2.

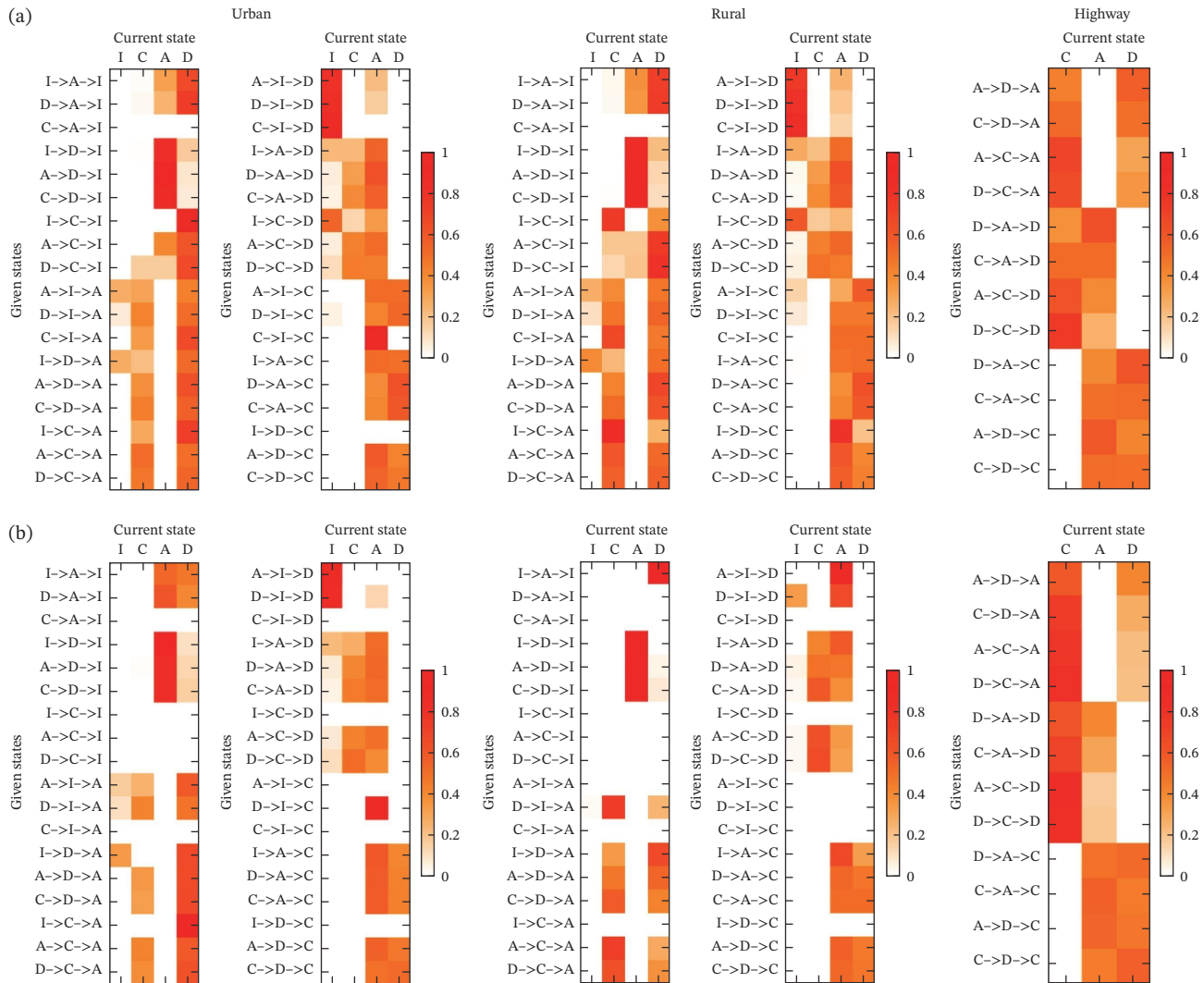


FIGURE 11 | Heatmaps of state transition matrix for different road types: driving data for (a) EV #1 and (b) EV #2.

acceleration, and road slope. Note that this model serves to effectively re-estimate torque in connecting sections that arise when linking the current driving cycle with the next driving segment. In the second step, the discharging current profile is derived from the required profile for motor power through an electrical conversion process that considers both the power efficiency and OCV

(Figure 1). Figure 13 illustrates the process of converting the power profile into the current profile. First, the required profile for LIB pack power is estimated based on the profile for motor torque, the profile for motor RPM, and the power efficiency (Figure 13(1)). Second, the SOC is derived based on the power consumption-based Coulomb-counting method with the profile

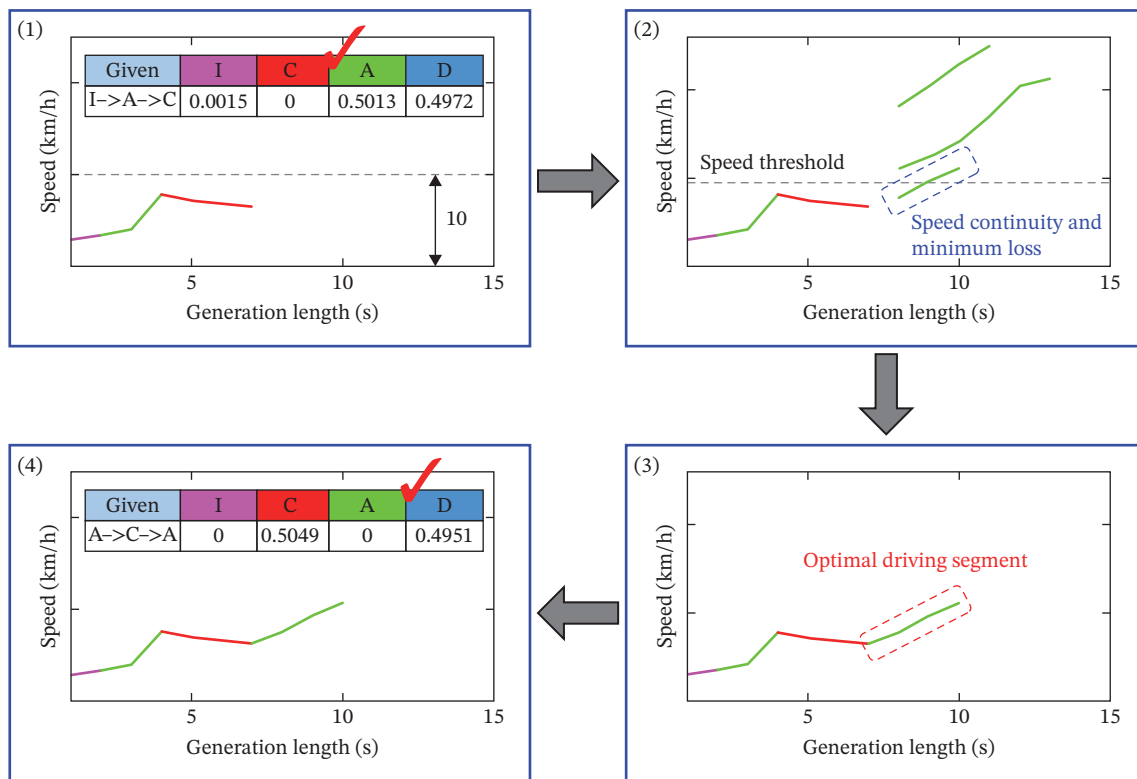


FIGURE 12 | Generation process of the representative driving cycle.

for LIB pack power, and the corresponding OCV is determined from the derived SOC (Figure 13(2)). Third, the profile for the LIB pack current is converted by dividing the profile for the LIB pack power by the corresponding OCV (Figure 13(3)). Hence, this conversion process generates a discharging current profile suitable for degradation experiments by considering the electrical driving characteristics of the EV of interest.

4.2 | Characteristics of Stochastically Generated Dynamic Driving

The fitness of the proposed method for generating the operational profile is evaluated by comparing the dynamic characteristics of the generated driving cycles corresponding to the driving data for each road type of both EV #1 and #2. The relative error and root mean squared error (RMSE) are addressed as the quantitative metrics in this analysis.

First, the representative driving cycles generated for EV #1 are shown in Figure 14a. The characteristics of representative driving cycles vary depending on the road type. Specifically, frequent stops occur in urban and rural road types, whereas continuous high-speed driving is maintained in the type of highway road because these different features are inherent characteristics of driving cycles for each road type. The relative error of each driving characteristic is calculated to demonstrate that the generated speed profiles should represent field driving cycles (Figure 14b). Remarkably, the representative driving cycles show the maximum, mean, and minimum relative errors of 6.01%, 1.35%, and 0.0001%, suggesting that the virtual driving cycles well replicate field driving cycles for all road types. Note that the generated driving cycles satisfy the representativeness criterion that requires all dynamic driving characteristic errors to be below

10% [40] (Table 6). The similarity in distribution between the representative driving cycles generated and driving data for EV #1 is also analyzed through the joint distribution of speed and acceleration frequency (Figure 14c). Specifically, inset figures in the first row in Figure 14c present the joint distribution of the representative driving cycles generated, whereas those in the second row in Figure 14c present the joint distribution of the driving data for EV #1. The RMSEs between the two joint distributions are 0.21%, 0.22%, and 0.48% for urban, rural, and highway road types, respectively, implying that a high level of similarity is secured between the two joint distributions for all road types. These results suggest that the proposed method effectively generates representative driving cycles for each road type, corresponding to the driving data for EV #1.

Second, Figure 15 shows that the proposed method also well generates representative driving cycles corresponding to EV #2, which is 34 times sparser than EV #1. Note that the characteristics of the representative driving cycles are similar to those of the analysis of EV #1. Specifically, frequent stops occur in urban and rural road types, whereas continuous high-speed driving is maintained in the type of highway road (Figure 15a). The relative error of each driving characteristic is also below 10% for all road types (Table 6), implying that the virtual speed profiles would effectively represent field driving cycles (Figure 15b). Remarkably, the representative driving cycles show the maximum, mean, and minimum relative errors of 6.14%, 2.29%, and 0.11%, even though data for EV #2 is sparser than that for EV #1, confirming that the driving cycles generated from the proposed method well replicate field driving cycles. The similarity in distribution between the representative driving cycles generated and driving data for EV#2 is further analyzed through the joint distribution of speed and acceleration frequency (Figure 15c). The RMSE

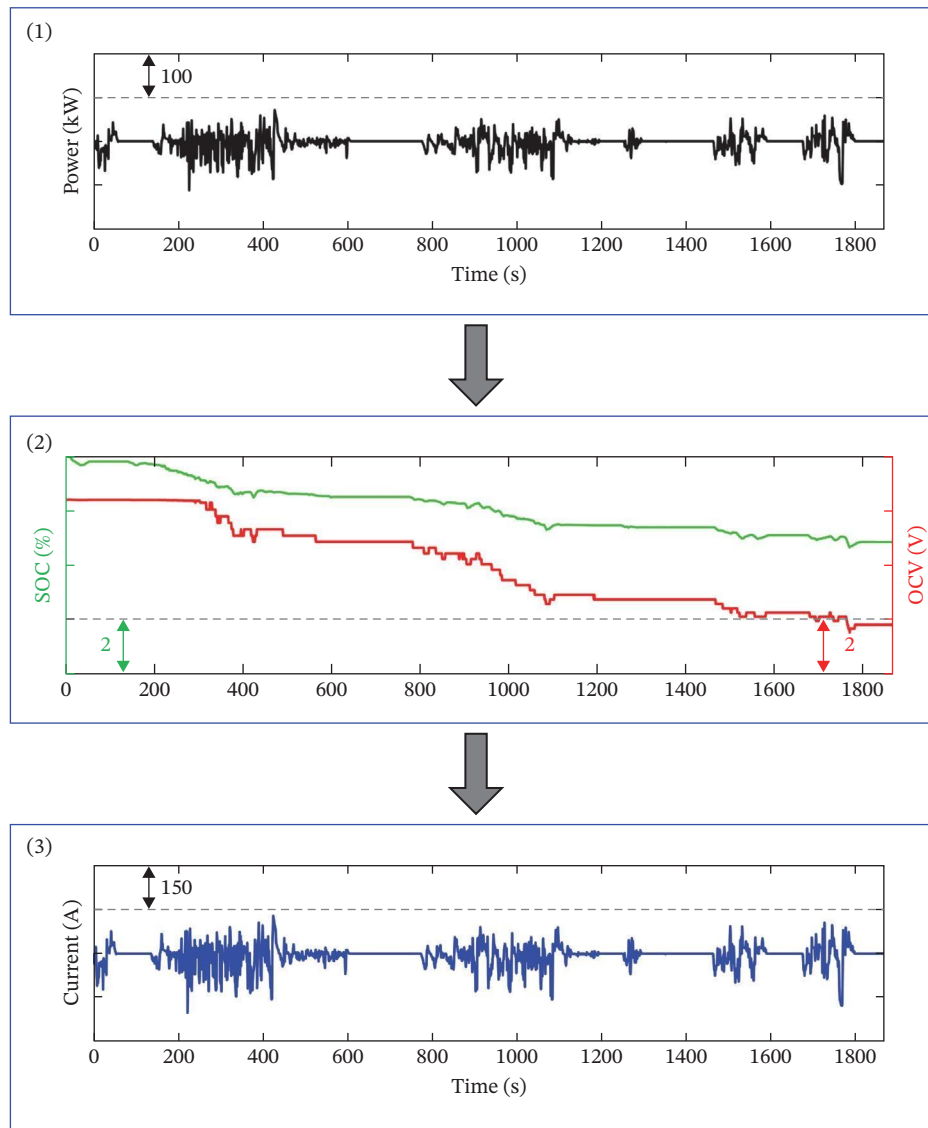


FIGURE 13 | Conversion process from power profile to current profile.

between the two joint distributions shows a maximum value of 0.62% for the type of highway road, securing a high level of similarity for all road types. In conclusion, the proposed method effectively generates representative driving cycles for each road type corresponding to the driving data for EV #2, even under sparse-data conditions.

Third, Fourth, the effectiveness of BO to select the optimal weights corresponding to each dynamic driving characteristic in the object function (Equation (9)) is validated by repeating the proposed method 10 times. This study proposes a BO-based weight optimization approach to consider the relative importance of each dynamic driving characteristic, thereby enabling the generation of multiple representative driving cycles. Previous studies mainly employed uniform weights for all dynamic driving characteristics in the objective function for generation of representative driving cycles, having limitations in considering the relative importance of each dynamic driving characteristic [40, 41]. The proposed method addresses these limitations by optimizing weights corresponding to each dynamic driving characteristic based on the BO. The repeatability of the proposed method

related to performance on generation of multiple representative driving cycles is analyzed based on the mean relative errors of all the dynamic driving characteristics for each repeatedly generated driving cycle (Figure 16). Note that all weights were set to unity in the case that BO was not executed in this comparison. Interestingly, the representative driving cycles with optimal weights show the maximum, mean, and minimum relative errors of 9.80%, 2.35%, and 0.0001% for EV #1 and 9.97%, 3.60%, and 0.01% for EV #2. It is worth noting that all 10 driving cycles generated corresponding to both driving data satisfy the criterion of having a mean relative error below 10%, with no outliers exceeding the threshold. In contrast, most of the driving cycles generated fail to satisfy the representativeness criterion in the case that BO was not executed. This comparison clearly suggests that optimal weights in the object function would be effective in reflecting the inherent variability of field driving cycles by considering the relative importance of each dynamic driving characteristic. Hence, the proposed method is demonstrated to effectively replicate the variability and diversity of field driving cycles through the generation of distinct representative driving cycles at each time based on optimal weights.

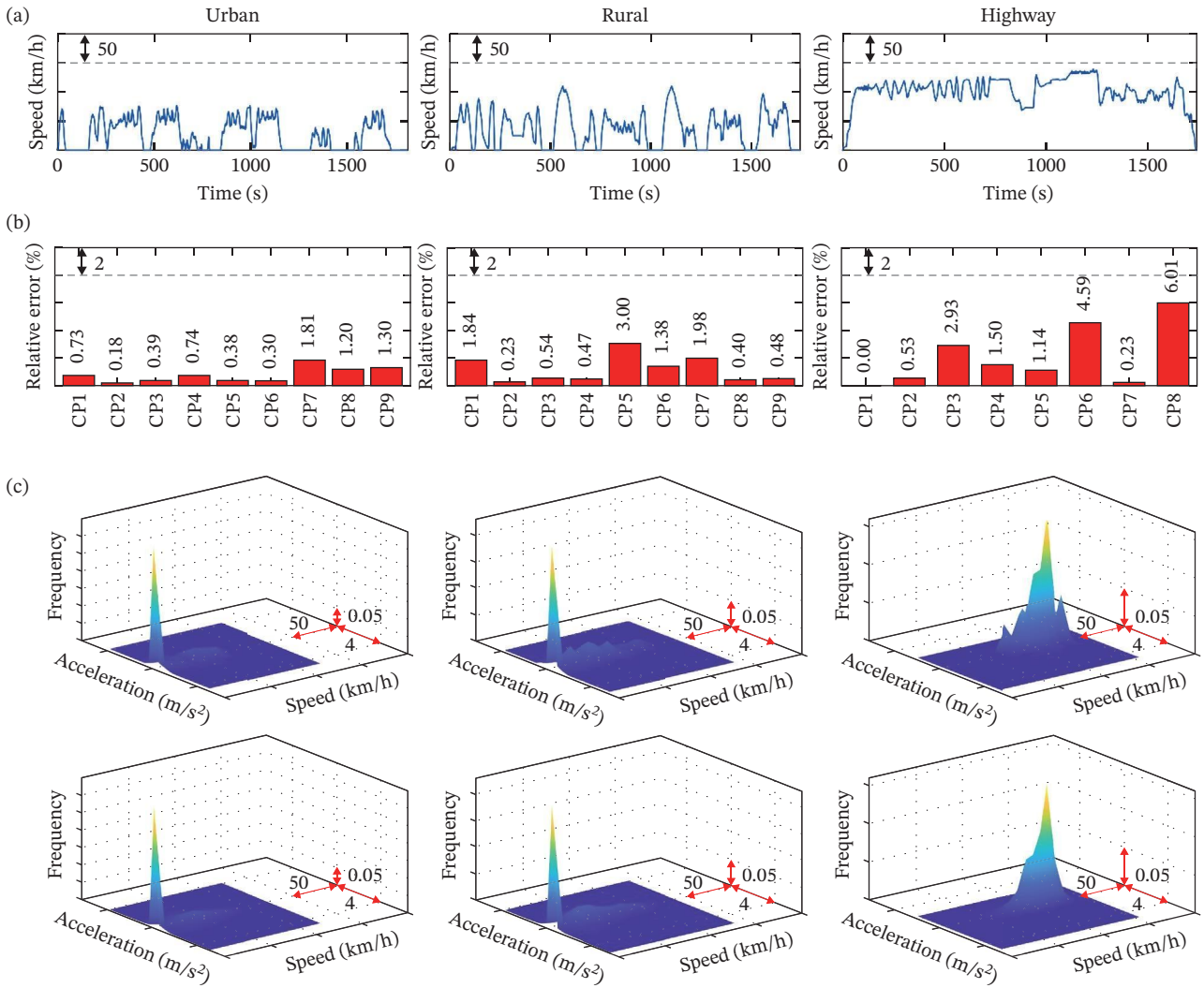


FIGURE 14 | Generation results corresponding to the driving data for EV #1: (a) representative driving cycles, (b) relative errors of each characteristic parameter, and (c) joint distributions of acceleration and speed.

4.3 | Fidelity of Converted Electric Profiles

This subsection evaluates the feasibility of the proposed method by analyzing the energy consumption of the converted electric profiles. Note that the energy consumption is estimated by dividing the integral of the power over time by the total driving distance. The relative error was also calculated for quantitative comparison. Note that the conversion method from a driving cycle to an electric profile aims to generate the virtual current profile required for the discharging process of LIBs in EVs. Hence, the final current profile should reflect the actual operational conditions of driving cycles.

First, the electric profiles converted for both EVs are analyzed, as shown in Figure 17. Specifically, the first row in Figure 17a,b presents the power profiles converted for both EVs, whereas the second row in Figure 17a,b presents the current profiles converted under the assumption of an initial SOC of 100%. Interestingly, the magnitude of the power profiles is higher in the type of highway road compared to those in urban and rural road types for both EVs. This observation can be explained by the fact that aerodynamic drag force $\frac{1}{2}\rho_{\text{air}}A_fC_Dv^2(t)$ serves as the dominant resistance as speed increases [54], thereby requiring the relatively

higher power for vehicle operation in the type of highway road. The relative errors of the energy consumption corresponding to each road type are calculated (Table 7). Specifically, the errors of urban, rural, and highway are 4.37%, 1.73%, and 6.52% for EV #1 and 7.43%, 7.07%, and 3.91% for EV #2, respectively. These results suggest that the virtual power profiles accurately replicate actual energy consumption for all road types, with all relative errors remaining below 10%. Note that the acceleration term serves as a major physical factor in power calculation (Equation (11)) in that mean optimal weights for a_{avg} and d_{avg} are 8.7 and 6 for EV #1, and 8.3 and 8.7 for EV #2 (Table 6). This analysis highlights the importance of replicating acceleration-related characteristics measured in actual driving data because these values secure the high fidelity of the converted power profiles. Hence, the proposed method effectively estimates the virtual power profiles corresponding to generated driving cycles, showing high suitability for converting them into current protocols for the discharging process under actual driving.

Second, the effectiveness of an estimated road slope (Equation (12)) in battery power calculation is validated through a comparison between the LIB pack power, which is derived from

TABLE 6 | Evaluation result of representativeness of generated driving cycle corresponding to the driving data for two EVs.

Driving data	Characteristic parameter	Weight	Ground truth	Driving cycle	RE (%)	RMSE (%)
EV #1—urban	v_{avg} (km/h)	1	26.81	26.61	0.73	0.21
	v_{std} (km/h)	3	25.48	25.43	0.18	
	a_{avg} (m/s ²)	8	0.68	0.68	0.39	
	d_{avg} (m/s ²)	7	−0.60	−0.60	0.74	
	RPA (m/s ²)	1	0.32	0.32	0.38	
	r_{idling}	7	0.3452	0.3442	0.30	
	r_{cruise}	3	0.0979	0.0997	1.81	
	$r_{acceleration}$	6	0.2650	0.2682	1.20	
	$r_{deceleration}$	4	0.2918	0.2880	1.30	
EV #1—rural	v_{avg} (km/h)	2	37.37	36.68	1.84	0.22
	v_{std} (km/h)	1	29.83	29.76	0.23	
	a_{avg} (m/s ²)	9	0.62	0.62	0.54	
	d_{avg} (m/s ²)	4	−0.58	−0.58	0.47	
	RPA (m/s ²)	1	0.29	0.30	3.00	
	r_{idling}	10	0.2256	0.2225	1.38	
	r_{cruise}	9	0.1355	0.1382	1.98	
	$r_{acceleration}$	7	0.3103	0.3091	0.40	
	$r_{deceleration}$	8	0.3287	0.3303	0.48	
EV #1—highway	v_{avg} (km/h)	6	105.62	105.6201	0.0001	0.48
	v_{std} (km/h)	2	15.62	15.54	0.53	
	a_{avg} (m/s ²)	9	0.30	0.31	2.93	
	d_{avg} (m/s ²)	7	−0.29	−0.29	1.50	
	RPA (m/s ²)	7	0.14	0.14	1.14	
	r_{cruise}	10	0.4136	0.4326	4.59	
	$r_{acceleration}$	5	0.2828	0.2822	0.23	
	$r_{deceleration}$	8	0.3035	0.2853	6.01	
EV #2—urban	v_{avg} (km/h)	2	24.57	24.43	0.59	0.25
	v_{std} (km/h)	1	22.62	21.79	3.68	
	a_{avg} (m/s ²)	9	0.57	0.59	2.76	
	d_{avg} (m/s ²)	9	−0.56	−0.56	0.87	
	RPA (m/s ²)	1	0.28	0.29	5.64	
	r_{idling}	7	0.2857	0.2854	0.11	
	r_{cruise}	8	0.1045	0.1023	2.08	
	$r_{acceleration}$	9	0.3055	0.2968	2.86	
	$r_{deceleration}$	8	0.3043	0.3155	3.69	
EV #2—rural	v_{avg} (km/h)	2	52.67	51.58	2.07	0.40
	v_{std} (km/h)	2	32.05	32.14	0.28	
	a_{avg} (m/s ²)	9	0.46	0.45	0.37	
	d_{avg} (m/s ²)	10	−0.48	−0.48	0.29	
	RPA (m/s ²)	1	0.21	0.22	3.30	

(Continues)

TABLE 6 | (Continued)

Driving data	Characteristic parameter	Weight	Ground truth	Driving cycle	RE (%)	RMSE (%)
EV #2—highway	r_{idling}	7	0.1418	0.1397	1.51	0.62
	r_{cruise}	8	0.2119	0.2249	6.14	
	$r_{\text{acceleration}}$	4	0.3310	0.3191	3.59	
	$r_{\text{deceleration}}$	3	0.3154	0.3163	0.29	
	v_{avg} (km/h)	1	116.36	112.64	3.20	
	v_{std} (km/h)	1	16.13	16.2	0.44	
	a_{avg} (m/s ²)	7	0.22	0.23	3.75	
	d_{avg} (m/s ²)	7	−0.21	−0.21	1.31	
	RPA (m/s ²)	3	0.10	0.11	5.14	
	r_{cruise}	8	0.5297	0.5387	1.71	
	$r_{\text{acceleration}}$	5	0.2272	0.2194	3.43	
	$r_{\text{deceleration}}$	8	0.2431	0.2419	0.51	

the speed and acceleration measurements in actual driving data, and field-measured LIB pack power. Note that all road slopes were set to zero in the case that the estimated road slope was not considered in this quantitative comparison. The accuracy of the proposed method is analyzed based on the normalized RMSE (NRMSE) by dividing the RMSE of LIB pack power by the max power in consideration of the large order of LIB pack power (Table 8). Remarkably, the LIB pack powers calculated with the estimated road slope show the maximum, mean, and minimum NRMSE of 3.32%, 4.81%, and 7.02% for EV #1 and 2.63%, 3.00%, and 3.23% for EV #2. In contrast, the LIB pack powers calculated without road slope show a mean NRMSE of 12.67% for EV #1 and 9.28% for EV #2. This comparison indicates that the estimated road slope contributes to improve 2.63 and 3.09 times in the mean accuracy for each EV. This analysis clearly suggests that the virtual road slope in LIB pack power calculation should be considered to estimate the required driving force under field environments. Note that road slopes serve as a major factor in estimating the frictional force, reflecting the gravitational component in the calculation of the required LIB pack power (Equation (11)). Specifically, the frictional force should be increased due to additional resistance generated under a positive road slope, whereas the frictional force should be decreased as gravity assists the driving force under a negative road slope. Hence, the proposed method is effective to estimate the frictional force required for driving using virtual road slopes, thereby calculating the required power corresponding to the generated driving cycles with high fidelity.

4.4 | Superiority of the Proposed Framework

This subsection discusses the superiority of the proposed framework by comparing the daily durability evaluation time between the actual durability driving tests and the scenario proposed for the stochastic degradation experiment.

First, the implementation results of the scenario proposed for the stochastic degradation experiment corresponding to the randomly selected road type are presented (Figure (18)). In brief, the operational profile (the green dashed box in Figure 18) is

generated corresponding to a selected road type, with a length of 1866 s and an SOC reduction of 3.4758% (Equation (15)) per profile. Note that the scenario of a degradation experiment corresponding to the selected road type is defined as the charging pattern of one mid-driving charge followed by a postdriving charge (the red dashed box in Figure 18). In addition, the SOC range of mid-driving charge is sampled as 30.5% to 90.0%, whereas the SOC range of postdriving charge is sampled as 34.4% to 100.0% (the yellow dashed box in Figure 18). Note also that the repetition numbers of a discharging profile preceding each charging process are calculated as 20 and 16 by using Equation (3).

Second, the superiority of the scenario proposed for the stochastic degradation experiment is validated by analyzing the daily durability evaluation time based on the actual durability driving tests. Specifically, the mean daily durability driving evaluation time corresponding to EV #1 is 7.65, 7.49, and 7.25 h for urban, rural, and highway road types, respectively. In contrast, the proposed degradation scenario replicates durability driving conditions equivalent to a driving distance of 484.41 km over a total duration of 22.47 h under laboratory conditions. This result suggests that the proposed degradation scenario improves evaluation efficiency by accelerating durability testing, enabling ~2.94 times more evaluation per day. This difference suggests that actual durability driving tests require drivers to conduct long-distance driving for each test, posing challenges in maintaining continuous operation without rest. Hence, the proposed framework serves as a practical durability evaluation solution that enables continuous testing under controlled laboratory conditions without temporal limitations.

The proposed framework further enables quantitative analysis of the degradation behavior of LIBs in EVs with respect to the accumulated driving distance. Note that the operational profile used in the discharging process is generated based on actual driving data, with each profile corresponding to a specific driving distance. Hence, the proposed framework could be used to directly analyze the correlation between LIB degradation and accumulated driving distance, thereby applying practical evaluation of operational criteria, including the driving distance warranty.

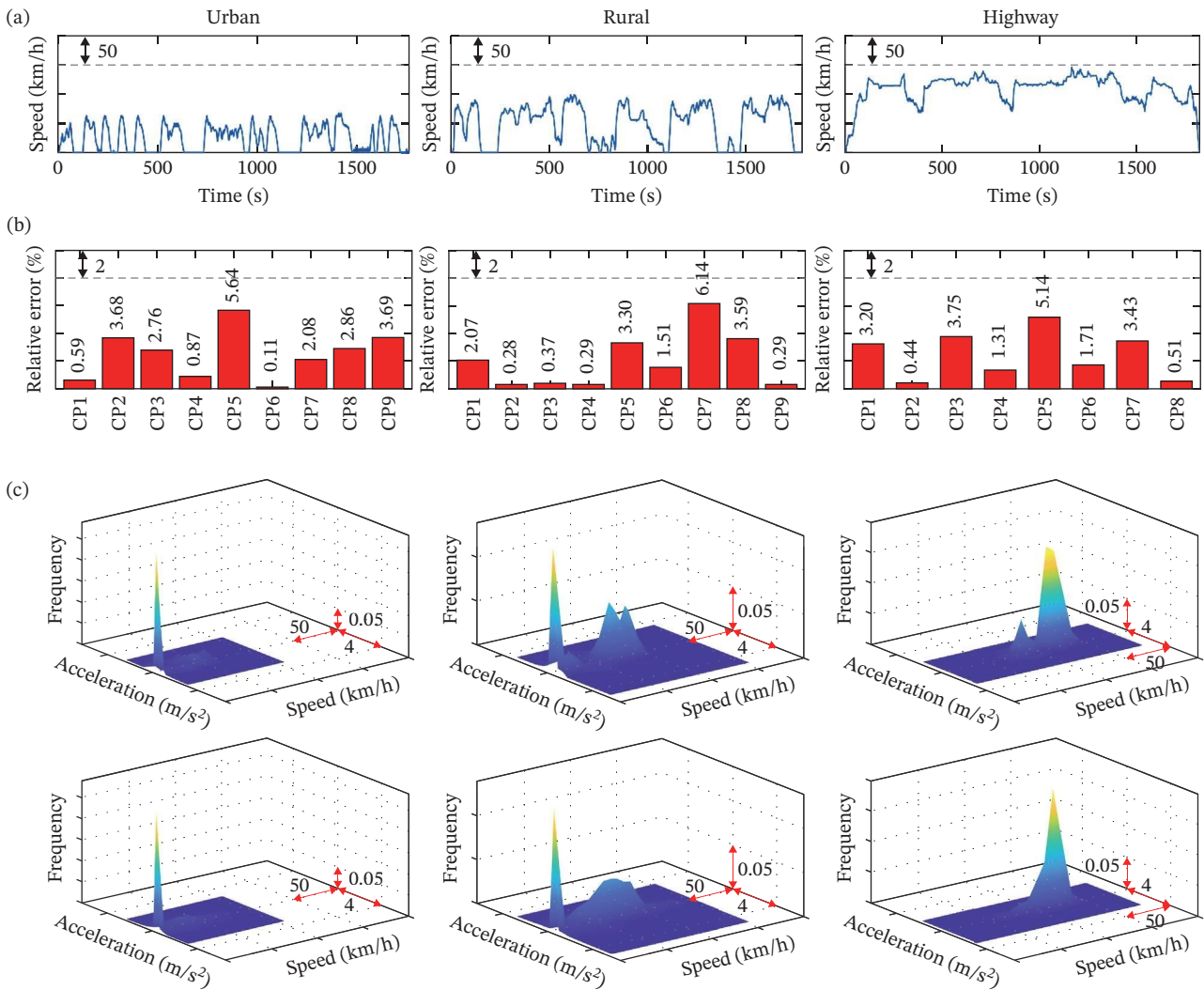


FIGURE 15 | Generation results corresponding to the driving data for EV #2: (a) representative driving cycles, (b) relative errors of each characteristic parameter, and (c) joint distributions of acceleration and speed.

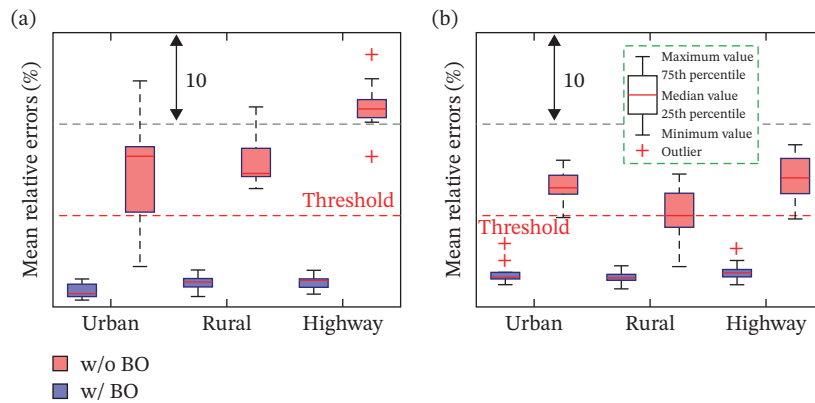


FIGURE 16 | Box plot of the mean relative errors with and without optimal weights: the driving data for (a) EV #1 and (b) EV #2.

5 | Conclusions

This study proposes a stochastic degradation experiment framework to quantitatively characterize the degradation pathway of LIBs in EVs under actual operational conditions. The proposed framework aims to design scenarios for stochastic degradation experiments corresponding to each road type based on the

analysis of actual durability driving test data and to generate operational profiles that represent the driving characteristics of dynamic discharging processes. The scenario for the stochastic degradation experiment is established based on the analysis of dominant charging patterns and statistical SOC ranges observed for each road type. This scenario replicates the

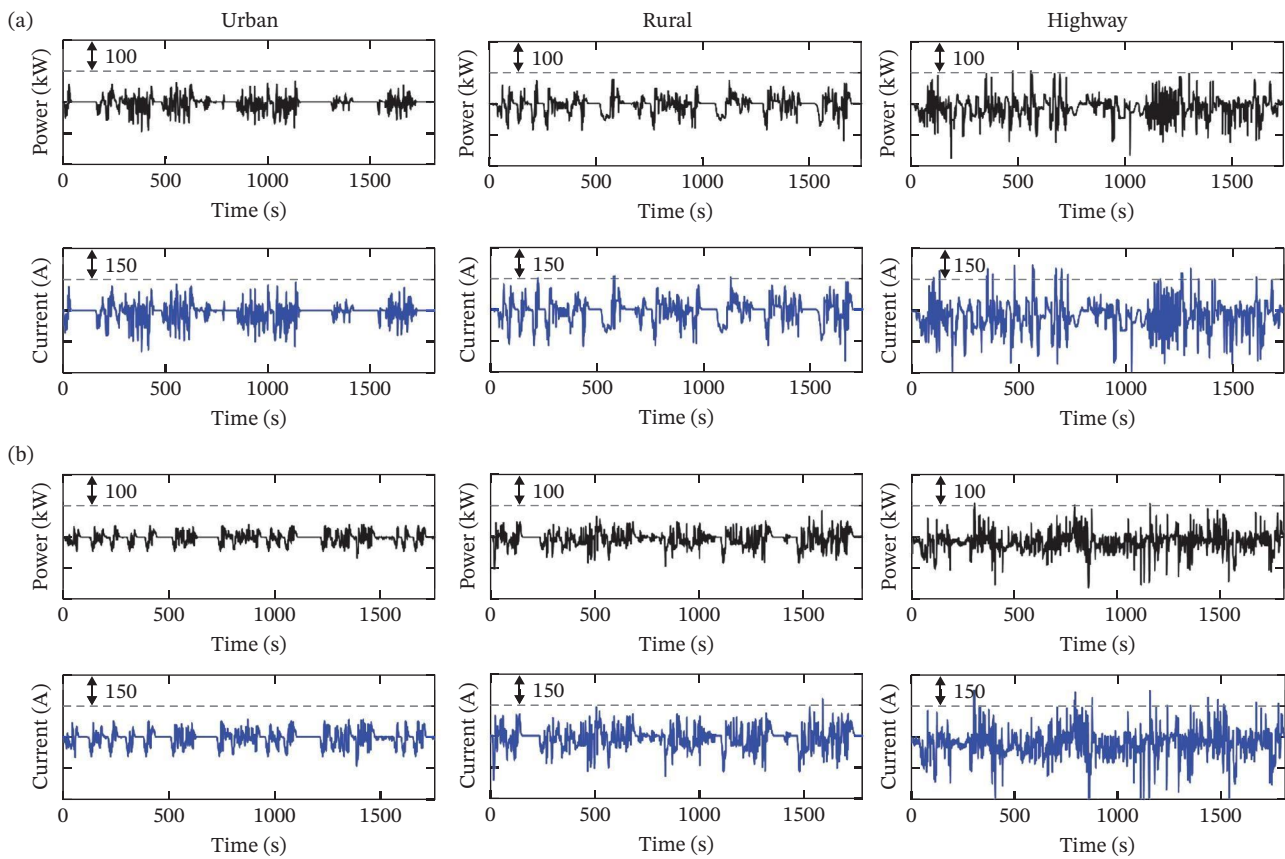


FIGURE 17 | Conversion results correspond to the driving data for (a) EV #1 and (b) EV #2.

TABLE 7 | Evaluation result of the feasibility of converted electric profile corresponding to the driving data for two EVs.

Test vehicle	Road type	Energy consumption (Wh/km)		RE (%)
		Ground truth	Electric profile	
EV #1	Urban	138.67	144.73	4.37
	Rural	130.70	128.44	1.73
	Highway	144.71	135.28	6.52
EV #2	Urban	102.48	110.10	7.43
	Rural	135.57	145.16	7.07
	Highway	235.93	226.70	3.91

charging patterns resulting from stochastic battery consumption for each road type and considers the variability of SOC ranges observed in actual durability driving tests into the experimental design. The operational profile required for the discharging process is further generated through the proposed generation method, which could replicate the dynamic power loads in field environments. Quantitative analysis of driving characteristics demonstrates that the generated operational profiles show high fidelity in terms of both dynamic and electrical driving characteristics. Specifically, the results show a mean relative error of 1.82% in the dynamic driving characteristics and 5.17% in the electrical driving characteristics. The implementation result of the degradation experiment with the proposed framework further achieves 2.94 times higher

efficiency in terms of time and labor consumption compared with field experiments. This achievement demonstrates the superiority of the proposed framework in designing degradation experiments replicating actual operational conditions. Future work will focus on examining degradation experiments based on the proposed framework and evaluating the validity of the framework by analyzing the quantitative correlation with the degradation pathway of the actual LIB pack in EVs. In addition, more extensive charging measurements under field durability tests will be further collected to validate the SOC sampling approaches based on the normal distribution assumption. Ultimately, this study aims to establish an evaluation system suitable for characterizing the degradation pathway of LIBs in EVs under stochastic operational conditions.

TABLE 8 | Calculation result of required LIB pack power with and without estimated road slope corresponding to the driving data for two EVs.

Test vehicle	Road type		Max power (kW)	RMSE (kW)	NRMSE (%)
EV #1	Urban	W/ road slope	123.13	4.09	3.32
		W/o road slope		12.15	9.87
	Rural	W/ road slope	123.93	5.06	4.08
		W/o road slope		15.41	12.44
	Highway	W/ road slope	126.88	8.91	7.02
		W/o road slope		19.91	15.69
EV #2	Urban	W/ road slope	130.46	4.21	3.23
		W/o road slope		9.34	7.16
	Rural	W/ road slope	172.45	4.53	2.63
		W/o road slope		14.67	8.51
	Highway	W/ road slope	170.41	5.36	3.14
		W/o road slope		20.76	12.18

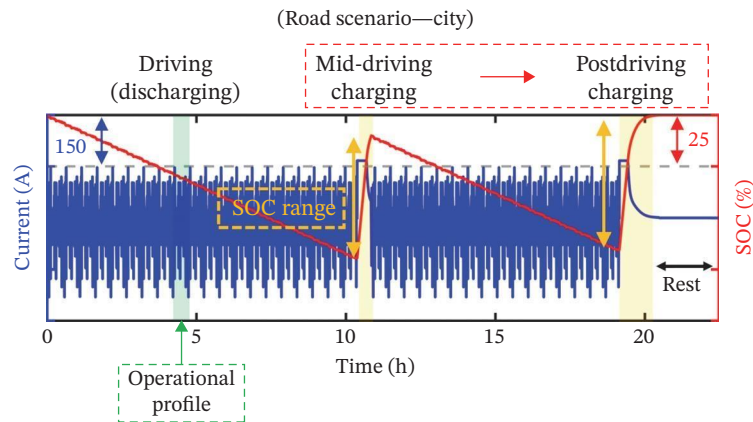


FIGURE 18 | Detailed implementation result of the scenario for a stochastic degradation experiment.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

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

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Appendix A. Estimation of Pack-Level OCV

The LIB pack OCV, considering actual operational conditions, was derived based on OCV measurement data obtained from low-current experiments on the LIB modules embedded in each EV. OCV measurements were conducted using a piece of 111.2 Ah NMC LIB module (2P6S) taken from each EV. Each LIB module was charged at 0.3C in CCCV mode, followed by a 2 h relaxation, discharge at 0.3C in CC mode, then followed by another 2 h relaxation. The voltage, accumulated ampere-hours during discharging, and accumulated ampere-hours during charging were recorded at 1 s intervals [55]. The total charged and discharged capacities were calculated using the Coulomb-counting method, and the SOC with respect to the total charged and discharged capacities were estimated at 1% SOC intervals, resulting in the OCV with respect to SOC. Pseudo OCVs were estimated using a weighted combination of the charged and discharged OCVs to compensate for the effect of OCV hysteresis, as follows [56]:

$$\text{OCV}(\text{SOC}) = V_{\text{charge}}(\text{SOC}) \times \frac{100 - \text{SOC}}{100} + V_{\text{discharge}}(\text{SOC}) \times \frac{\text{SOC}}{100}, \quad (\text{A.1})$$

where V_{charge} and $V_{\text{discharge}}$ denote the charged and discharged voltage. The OCV with respect to SOC is estimated by multiplying linear weight

voltage data in that the charged voltages of the LIB modules are dominant under the region of SOC above 50%. In contrast, the discharged voltages of the LIB modules are dominant under the region of SOC below 50%. Note that OCV is averaged from charged and discharged voltages at 50% SOC of the LIB modules. The pack-level OCV is estimated using the module-level pseudo OCV data, accounting for the series configuration of each EV. Note that the LIB packs embedded in each EV used in this study consisted of 22 and 32 series-connected LIB modules, as listed in Table 1. Hence, the pack-level OCVs for each EV were derived by scaling up the module-level OCV data by factors of 22 and 32, based on Kirchhoff's Voltage Law (KVL) in which voltage accumulates in series connections [57].

Appendix B. Theory of the BO

BO employs a probabilistic model to optimize hyperparameters based on Bayes' theorem as follows:

$$P(S|X) = \frac{P(X|S)P(S)}{P(X)}, \quad (\text{B.1})$$

where X and S denote observed data and hypothesis, respectively. $P(S|X)$, $P(X|S)$, $P(S)$ and $P(X)$ denote the posterior probability, likelihood, prior probability, and marginal probability, respectively. posterior probability $P(S|X)$ is updated by multiplying the prior probability $P(S)$ with the likelihood $P(X|S)$, and then is normalized by the marginal probability $P(X)$. The BO algorithm is conducted based on Bayes' theorem (Equation (B.1)) according to the following pseudo-code.

ALGORITHM A1 | Pseudo-code of the BO.

1. being procedure
2. for iterations $i = 1: N$ do
3. find i th sample (x_i) through optimizing U over $G(x_i)$
4. $G(x_i) = g(x_i)$
5. update the posterior of $G(x_i)$
6. end for
7. repeat
8. end procedure

where $G(x)$ and U denote objective function and acquisition function, respectively. BO combines the prior distribution of the objective function $G(x)$ with observed data to derive the posterior distribution. Note that this posterior informs the selection of the next sampling point by maximizing an acquisition function U to guide the search toward the minimum of the objective function.