Numerical Energy Analysis of In-Wheel Motor Driven Autonomous Electric Vehicles

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Abstract— Autonomous electric vehicles (EVs) are being widely studied nowadays as the future technology of ground transportation, while their conventional powertrain systems limit their energy efficiencies and may hinder their broad applications in the future. Here, we report a study on the energy consumption, efficiency improvement, and greenhouse gas (GHG) emissions of a mid-size autonomous EV (AEV) driven by in-wheel motors (IWMs), through the development of a numerical energy model, validated and implemented in a case study. The energy analysis was conducted under three driving conditions: flat road, upslope, and downslope driving, considering autonomous driving patterns, motor efficiency optimization, and regenerative braking. The case study based on the baseline EV driving data in West Los Angeles showed that an IWM-driven AEV can save up to 17.5% of energy during slope driving. In addition, it can reduce around 5.5% of GHG emissions annually in each state in the United States. Using the efficiency maps of a commercial IWM, the energy model and validated results in this study are in line with actual situations and can be used to support the future development of energy-efficient AEVs and sustainable energy transitions in ground transportation.

Index Terms— Autonomous electric vehicles (AEVs), energy efficiency, greenhouse gas (GHG) emissions, in-wheel motor (IWM), predictive modeling.

Nomenclature

\( a_s \) Vehicle acceleration (m \( \cdot \) s\(^{-2} \)).
\( A \) Frontal area (m\(^2\)).
\( b \) Constant in the derivation.
\( B_g \) Peak flux density in the air gap.
\( B_j \) Peak flux density in the stator teeth.
\( B_l \) Peak flux density in the stator yoke.
\( C_D \) Drag coefficient.
\( D_{e,s} \) Annual travel distance in each state (km).
\( D_{cycle} \) Driving distance of each driving cycle (km).
\( D_i \) Inner diameter of the stator (m).
\( D_o \) Outer diameter of the stator (m).
\( E \) Energy consumption per km (Wh).

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\( E_{reg} \) Regenerated energy per km (Wh).
\( E_{unit} \) Unit energy consumption for each driving cycle (Wh).
\( E_{SSCM} \) Energy consumption of the SSCM system (Wh).
\( E_{fraction} \) Energy consumption of the traction system (Wh).
\( f_r \) Road friction coefficient.
\( F_g \) Slope resistance (N).
\( F_a \) Acceleration resistance (N).
\( F_r \) Rolling resistance (N).
\( F_d \) Aerodynamic resistance (N).
\( F_{dem} \) Demanding traction force (N).
\( GHG_s \) Annual GHG emissions (kg CO\(_2\) eq.).
\( k \) Constant in the derivation.
\( k_w \) Fundamental winding factor.
\( K_{sp} \) Fundamental linear current density (A \( \cdot \) m\(^{-1} \)).
\( K_{fill} \) Filling factor.
\( L \) Length of stator lamination (m).
\( L_{ew} \) End-winding length (m).
\( m_c \) Mass of the cargo (kg).
\( m_e \) Baseline EV mass (kg).
\( m_o \) IWM-AEV mass (kg).
\( n \) Rotating speed of wheels (rpm).
\( p \) Number of pole pairs.
\( P_{ca} \) Stator copper loss (W).
\( P_{fe} \) Electromagnetic power (W).
\( P_{mag} \) Rotor magnet loss (W).
\( P_{recovery} \) Energy recovery of the traction system (kW).
\( P_{SSCM} \) Power demand of the SSCM system (kW).
\( P_{traction} \) Power demand of the traction system (kW).
\( r_d \) Tire rolling radius (m).
\( T_{dem,1} \) Upslope and flat road demanding traction torque (N \( \cdot \) m).
\( T_{dem,2} \) Torque demand to balance the electric vehicle during braking (N \( \cdot \) m).
\( T_{r,s} \) Local and highway travel ratio in each state.
\( U_{G,s} \) Electricity GHG emission factor in each state (g/kWh).
\( v \) Vehicle driving speed (km \( \cdot \) h\(^{-1} \)).
\( V_{ol,t} \) Volume of the stator tooth.
\( V_{ol,y} \) Volume of the stator yoke.
\( \lambda \) Demanding energy factor.
\( \lambda_2 \) Regenerating energy factor.
\( \theta \) Slope angle.
\( \eta_b \) IWM braking efficiency.

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efficiency loss in the inverter, electric motor, and mechanical of the battery energy is lost due to the energy transmission system in the AEV, also consume energy [6]. In addition, part conditioning (HV AC) system, entertainment system, and lighting auxiliary devices, such as heating, ventilation, and air con-

the power to make the autonomous driving system work; the energy consumers in the AEV. For instance, SSCM needs to overcome the driving resistance. Despite the largest share of power from SSCM to control vehicle motions. For an AEV, most processes the real-time signal inputs from various sensors and onboard energy-consuming devices. The onboard computer computing module (SSCM). The battery provides power to all (battery), actuators (powertrain), and self-driving sensing and

In general, an AEV has advantages over a conventional EV in saving energy since the driver is eliminated, which reduces the mass of motion, and the auxiliary devices can be turned off when no passengers are inside. Besides, the dispatch of AEVs can be trip-specific under optimal control and can effectively shorten passenger searching time and driving distance [8].

Current energy-saving studies on AEVs focus on conventional powertrain systems, which have low energy efficiency and may hinder the broad applications of AEVs [9]. In recent years, an innovative drive technology called an in-wheel motor (IWM) has been investigated as an alternative technology to improve the transmission efficiency of the powertrain system. IWM is an electric motor fixed on the wheel hub, which integrates the powering, transmission, and braking systems inside, and directly drives the wheel [10]. Before the IWM layout, most EVs used the front-engine & front-wheel-drive (FF) layout and the front-engine & rear-wheel-drive layout (FR layout) [11], and past research on AEV powertrain energy efficiency was based on those conventional layouts [12], [13], [14].

IWM technology has great potential in reducing EV energy consumption according to recent research [15]. First, the IWM layout has a simple structure for high transmission efficiency. The transmission efficiency for the IWM layout can be improved by 8%–15% compared with the conventional FF layout [16]. Without using transmission parts, the vehicle will be lighter and have more space to support a larger battery pack, which can increase the driving range of the vehicle. IWMs also have a high braking energy recovery rate than other electric motors because they are directly connected to the wheels [17]. Second, a large number of energy-saving controllers have been designed and validated for IWMs to improve both vehicle stability and energy efficiency. For example, Zhai et al. [18] designed a continuous steering stability controller based on an energy-saving torque distribution algorithm for an EV with four independent-drive IWMs. The controller can improve vehicle steering stability and reduce energy consumption by 23.7% compared with the conventional servo and ordinary continuous controllers. Wu et al. [19] proposed a model predictive control (MPC) method for the four-wheel-driven EV to reduce the electronic control unit (ECU) calculation time and energy consumption based on the road slope information and found that the energy can be saved by 1.27% for the real road condition. Yone and Fujimoto [20] designed a range extension system for a four-IWM-driven EV by controlling the yaw rate and sideslip angle and reported that it can decrease energy consumption by 13.4% compared with the conventional driving pattern. Third, for IWM-driven vehicles, it is easy to detect real-time driving and braking forces between tires and road surfaces, and the complex torque allocation plans can be applied to the IWM layout to improve technical performance and energy efficiency [21], [22]. Gang et al. [23] proposed a torque distribution control method for EVs with four IWMs under urban driving conditions based on the motor efficiency map. Compared with a working condition that has an equal drive torque and a fixed-ratio regenerative braking force distribution for four wheels, this energy-saving control method can reduce the overall energy consumption by 7.4%.

I. INTRODUCTION

THE large-scale electrification of ground transportation will increase the global electric vehicle (EV) fleet to 245 million by 2030 according to the estimate of the International Energy Agency [1]. The rapid growth of the EV fleet will enable an energy transition of ground transportation from fossil fuels to energy storage technologies. Current EVs are all powered by lithium-ion batteries. The driving range of EVs is dependent on the capacity of the battery pack and the energy efficiency of the powertrain system. Increasing battery capacity and improving the energy efficiency of the powertrain system both can reduce the unit energy consumption of EV driving, hence extend the driving range of EVs, and finally reduce the associated greenhouse gas (GHG) emissions per unit driving distance.

The future of ground transportation is autonomous EVs (AEVs) that have attracted enormous interest in recent years as next-generation transportation technologies for reducing energy consumption and GHG emissions. AEVs are predicted to be widely deployed in the near future (e.g., ten years) according to multiple recent studies [2], [3], [4]. However, improving the energy efficiency of the AEV is still a challenge [5]. Compared with conventional EVs, AEVs are expected to be more energy-efficient due to their smooth self-driving and efficient routing by an autonomous control system. In general, an AEV has three key components: energy source (battery), actuators (powertrain), and self-driving sensing and computing module (SSCM). The battery provides power to all the onboard energy-consuming devices. The onboard computer processes the real-time signal inputs from various sensors and then generates commands of the driving routes and behaviors to be passed to actuators, which will follow the commands from SSCM to control vehicle motions. For an AEV, most of the battery energy is consumed by the traction system to overcome the driving resistance. Despite the largest share of the energy going to the wheels, there are also many other energy consumers in the AEV. For instance, SSCM needs the power to make the autonomous driving system work; the auxiliary devices, such as heating, ventilation, and air conditioning (HVAC) system, entertainment system, and lighting system in the AEV, also consume energy [6]. In addition, part of the battery energy is lost due to the energy transmission efficiency loss in the inverter, electric motor, and mechanical transmission system, such as the gearbox and driving shaft [7].
Jiang et al. [24] designed an optimal torque energy-saving allocation method for a small-size IWM-EV, which can save 117 and 426 kJ per km compared with four-wheel torque equal distribution and rear axle drive. In their study, a prototype IWM-EV was built, and a bench test was carried out to verify the validity of the method [24]. The IWM technology is expected to become the dominant powertrain structure in the future due to its better performance in mobility and reliability, simpler transmission system, more precise and independent torque control [25], and more compact chassis integration [26].

All these studies provide a solid theoretical foundation to support the sustainable transitions: from EV to AEV and from the conventional powertrain system to the IWM powertrain system, which grants IWM-AEVs great energy-saving potential. However, after our rigorous literature survey, we found that, currently, no study has been conducted on the IWM-driven AEV (IWM-AEV) to analyze its energy consumption pattern and potential in improving the energy efficiency of AEV systems. The impacts of autonomous driving and IWM powertrain techniques on the associated GHG emissions are also unknown. Although the aforementioned studies discussed the feasibility of improving IWM-EV’s energy efficiency by optimizing the torque distribution among each wheel and the road-wheel interaction based on the IWM model built in the software, such as CarSim [18], [19], [20], [21], [22], [23], these reported studies did not consider the mass increase of the IWMs and the SSCM. Their energy consumption and interactions with the powertrain system have not been analyzed and compared with those of conventional EVs either. Besides, the energy analysis and energy-saving design methods on reported IWM-EVs work only focused on circumstances, such as the double-lane-change maneuver in CarSim and urban driving cycles without slopes. The possibility of combining the technologies of IWM and AEV has not been discussed in the literature. In addition, most control methods reported are on light vehicle simulations using the IWMs with a maximum torque of less than 600 N·m, which does not meet the actual demand of a vehicle. Thus, there is currently a gap of knowledge between theoretical research and practical applications of the IWM-AEV system.

In this article, we presented a numerical analysis of driving energy for IWM-AEV. Using a mid-size passenger EV as the baseline, an AEV model was configured with commercial IWMs and SSCM systems. Two energy-determining factors, the demanding energy factor and regenerating energy factor, were proposed based on the adjusted IWM characteristic contours. Energy modeling of the IWM-AEV with various driving speeds was conducted to analyze the energy consumption under three road conditions: flat road, upslope, and downslope. Standard driving cycles and a case study in West Los Angeles with real travel data were used to demonstrate and validate the analysis results. The designed IWM-AEV can provide a maximum torque of 2500 N·m and a maximum driving speed of 192 km h⁻¹, which makes this study close to the actual vehicle applications, and the results can be useful to support the design of an energy-efficient IWM-AEV system in future. Based on actual driving distance and specific GHG emission factors, a comparison study between the conventional EV and the IWM-AEV on their annual GHG emissions in each state of the United States was conducted to reflect their environmental impacts and the contributions that IWM-AEV can make to the energy and sustainability transitions.

II. CONFIGURATION OF THE IN-WHEEL MOTOR AUTONOMOUS ELECTRIC VEHICLE

The IWM-AEV is configured by modifying a mid-size passenger EV with a conventional FF layout (front-engine, front-wheel-drive layout) in which the powertrain components are replaced and rearranged, as shown in Fig. 1. An 80-kW power and 280-N·m torque ac (alternating current) synchronous electric motor is replaced by two IWMs, each of which can provide 64-kW power and 500-N·m torque [39], [40]. The transmission axle and gearbox are removed, with an SSCM added. Taking the Ford Fusion autonomous vehicle test version as the benchmark [27], components in the SSCM system of the proposed IWM-AEV are listed in Table I.

Red dashed-dotted flow lines in Fig. 1 show the control relationship among the components in the driveline: the battery management system (BMS), which manages the lithium-ion battery pack for power inputs and outputs, and the ECU, which controls two IWMs. Black solid flow lines in Fig. 1 show the energy flow in the traction system: the electricity flows from the car charger to the wheels via the battery, the inverter, and the IWMs. The energy efficiency of the IWM-AEV was modeled based on the Argonne National Laboratory’s (ANL’s) experimental test of delivered energy from the EV supply equipment (EVSE) to wheels on a mid-size EV [37]. Table II lists the main parameters used for the IWM-AEV configuration in this study. Based on the literature [38], the weights of motors and transmission parts were set as 56 kg for an 80-kW motor and 70 kg for the transmission parts. Each IWM weighs 31 kg. Although the IWM-AEV system becomes lighter after removing the transmission parts, an SSCM is needed for autonomous driving, and it weighs 19 kg and consumes 240-W power. Based on the data provided by manufacturers [39], the total efficiency of transmission parts and the motor controller was calculated to be 91%.

III. NUMERICAL ENERGY ANALYSIS OF THE IWM-AEV DRIVING

A. Driving Conditions and Strategies for Energy Analysis

In this energy analysis, three driving conditions were considered: flat road, upslope, and downslope driving, being analyzed in two scenarios. The first scenario covers both upslope and flat road driving conditions as both rely on traction power to move the vehicle. The second scenario considers downslope driving, which requires braking and regenerates energy during driving.

Consistent with the typical assumptions in other existing literature about IWM-EVs and AEVs, the following assumptions were made in this study. First, the driver was eliminated in the IWM-AEV because the level of vehicle autonomy is assumed to be level 5: full driving automation, and no driver is needed to control the IWM-AEV. It is typical to have this assumption in AEV studies, such as [44] and [45].
Second, the HVAC system and other auxiliary systems were assumed to be turned off to save energy when there are no passengers in the IWM-AEV. This assumption is common in AEV energy studies, such as [46] and [47]. Third, the transmission efficiency and battery efficiency in the IWM-AEV were constant during driving because their change is too small in one trip, such as 0.0285% degradation per cycle [48]. The motor efficiency of the baseline EV was also constant at 89%. Most EV energy studies have this assumption, such as [7] and [32].

The energy consumed in the driving of a vehicle is governed by various resistances to overcome during the moving of the vehicle. In general, the resistance force of the vehicle consists of four parts: the slope resistance ($F_g$), the acceleration resistance ($F_a$), the rolling resistance ($F_r$), and the aerodynamic resistance ($F_d$) [49]. Before carrying out the energy analysis under the downslope condition, the relationships between the slope resistance and the sum of rolling resistance and aerodynamic resistance are benchmarked. If $F_g > (F_r + F_d)$, the electric motor will work in a braking status since the slope is steep enough to require braking. If $F_g = (F_r + F_d)$, the vehicle resistances are balanced, and no external forces are needed. Vice versa, if $F_g < (F_r + F_d)$, the electric motor will work in a motoring status, which is like driving the car under the upslope condition. Fig. 2 shows the AEV driving logic for energy analysis. The demanding traction force ($F_{dem}$) can be calculated based on vehicle dynamics. Considering the constraints of the IWM efficiency data, the speed points with high energy efficiency can be calculated for both energy consumption and energy regeneration curves. When the IWM-AEV works under upslope, flat road, and downslope motoring conditions, it should operate at the lowest energy consumption speed points. When the IWM-AEV works under the downslope braking condition, it recovers energy from the regenerative braking and should operate at the speed points with the highest energy regeneration. In addition, if vehicle resistances are balanced, the IWM-AEV can drive down the slope without any energy consumption.

![Overall structure of a mid-size IWM-AEV configured for this study.](image)

**TABLE I**

| Component                  | Model                          | Power (W) | Mass (kg) | Number | Reference |
|----------------------------|--------------------------------|-----------|-----------|--------|-----------|
| LIDAR                      | Velodyne VLP-16                | 8         | 0.83      | 2      | [28]      |
| Radar                       | Bosch LRR4                     | 4.5       | 0.24      | 2      | [29]      |
| Camera                      | Pt. Gray Dragonfly2            | 2.1       | 0.045     | 7      | [30]      |
| Sonar                       | Bosch Ultrasound               | 0.052     | 0.02      | 8      | [31]      |
| GPS                         | NovAtel PwrPak 7               | 1.8       | 0.51      | 1      | [32]      |
| V2X wireless communication module | Cohda MK5 module           | 2.1       | 0.01      | 1      | [33]      |
| Computer                    | Nvidia Drive PX2               | 98        | 5.075     | 2      | [34, 35]  |
| Wire harness and case       |                                | /         | 5.7       | /      | [36]      |
TABLE II
MAIN PARAMETERS USED IN THIS STUDY

| Parameter                                           | Value  | Units | References |
|-----------------------------------------------------|--------|-------|------------|
| Common in both baseline EV, IWM-AEV, and AEV without IWMs |        |       |            |
| Frontal area ($A$)                                   | 2.7435 | $m^2$ | [38]       |
| Drag coefficient ($C_D$)                             | 0.29   |       | [37]       |
| Inertia of rotating parts ($\delta_i \ast m_o$)      | 148    | kg    | [41]       |
| Tire rolling radius ($r_d$)                          | 0.31595| m     | [37]       |
| Battery charging efficiency ($\eta_c$)               | 86.7%  |       | [42]       |
| Battery discharging efficiency ($\eta_d$)            | 88.5%  |       | [42]       |
| Special in Baseline EV                               |        |       |            |
| Baseline EV mass ($m_o$)                             | 1481   | kg    | [37]       |
| Baseline EV transmission efficiency ($\eta_i^T$)     | 93%    |       | [37]       |
| Baseline EV inverter efficiency ($\eta_i^I$)         | 95%    |       | [40]       |
| Special in IWM-AEV                                  |        |       |            |
| IWM-AEV mass ($m_o$)                                 | 1436   | kg    | [40]       |
| IWM-AEV transmission efficiency ($\eta_i^T$)         | 99%    |       | [17]       |
| IWM braking energy recovery rate ($\eta_{\text{recover}}$) | 85%    |       | [39]       |
| IWM-AEV inverter efficiency ($\eta_i^I$)            | 97.4%  |       | [43]       |
| Special in AEV without IWMs                         |        |       |            |
| AEV mass ($m_{\text{AEV}}$)                         | 1500   | kg    | [37, 39]   |
| AEV transmission efficiency ($\eta_{\text{trans}}$) | 93%    |       | [37]       |
| AEV inverter efficiency ($\eta_{\text{in}}$)        | 95%    |       | [40]       |

Fig. 2. Logic of the energy-saving control for the IWM-AEV driving.

**B. IWM Efficiency**

The motoring and braking efficiency data were extracted from the official efficiency maps of the commercial IWM used in the IWM-AEV design [50] and were plotted into 3-D contours, as shown in Fig. 3(a) and (b). Both the motoring and braking efficiencies are determined by the torque and rotating speed during driving. The IWM efficiency varies from 0% to 91%, while the rotating speed and torque range from

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0 to 1600 rpm (from 0 to 192 km h\(^{-1}\) for the IWM-AEV) and 0 to 1250 N \cdot m, respectively. A small torque or a low speed will lead to low efficiency. High-efficiency areas are located in the middle of the torque and speed range. However, the IWM motoring efficiency map cannot be directly applied to the IWM-AEV energy analysis because the motor has not been tuned and optimized to make the vehicle operate in high-efficiency areas. Over half the area of the motoring efficiency map is lower than 80%. It cannot reflect the actual efficiency of the commercial IWM [see Fig. 3(a)] and falls in the range of 55% and 94.5% [53]. Here, we used the adjusted motoring efficiency map [see Fig. 3(c)] for the IWM-AEV operations.

From the adjusted results, the IWM’s maximum motoring efficiency is 94.5%, and most of the map area has a motoring efficiency higher than 60%. As shown in Fig. 3(c), the adjusted motoring efficiency map keeps the contour pattern of the commercial IWM [see Fig. 3(a)] and falls in the range of reported IWM efficiency in the literature between 55% and 94.5% [53]. Here, we used the adjusted motoring efficiency in our energy analysis of the IWM-AEV operations.

### C. Upslope and Flat Road Driving

With the configured IWM motoring efficiency, the energy consumption of the AEVs can be numerically determined for various driving conditions. Considering the flat road and upslope driving in the same scenario, the energy consumption of the AEV’s powertrain system from the battery to the wheels can be modeled as [54]

\[
E = E_{\text{traction}} + E_{\text{SSCM}}
\]

\[
E = \int P_{\text{traction}} dt + \int P_{\text{SSCM}} dt
\]

\[
= \int \frac{T_{\text{dem}} \cdot n \cdot \eta_d \cdot \eta_i \cdot \eta_m \cdot \eta_f \cdot v dt}{\eta_d \cdot \eta_i \cdot \eta_m \cdot \eta_f} + \int P_{\text{SSCM}} dt
\]

\[
= \frac{1}{\eta_d \cdot \eta_i \cdot \eta_m \cdot \eta_f} \left( \int F_d v dt + \int F_f v dt + \int F_g v dt + \int P_{\text{SSCM}} dt \right)
\]

where \(E\) (Wh) is the energy consumption per km, \(P_{\text{traction}}\) (kW) is the power demand of the traction system, \(P_{\text{SSCM}}\) (kW) is

\[
\eta_m = 1 - \frac{P_{\text{Cu}} + P_{\text{Fe}} + P_{\text{mag}}}{P_e}
\]

\[
P_{\text{Cu}} = \frac{\rho_{\text{Cu}} \cdot (L + L_{\text{ew}}) \cdot (K_{\text{fill}} \cdot D_i \cdot \eta_i) \cdot 2}{\pi \cdot \left( \frac{D_o^2}{4} \cdot (D_i + \frac{B_e \cdot D_o}{2B_p \cdot K_{\text{fill}}} \right)^2} - \frac{B_e \cdot D_o}{B_i} \left( \frac{D_o - D_i}{2} - \frac{B_e \cdot D_o}{4B_p \cdot K_{\text{fill}}} \right)
\]

\[
P_{\text{Fe}} = \rho_s \cdot (p_{\text{Fe}} \cdot (B_i) \cdot \text{Vol}_i + p_{\text{Fe}} \cdot (B_e) \cdot \text{Vol}_e)
\]

\[
P_{\text{mag}} = 2p \cdot L \cdot \sum_{n=1}^{\infty} (p_{\text{cn}} + p_{\text{an}})
\]
the power demand of the SSCM system, $T_{\text{dem,1}}$ (N · m) is the demanding traction torque, $n$ (rpm) is the rotating speed of wheels, $v$ (km h$^{-1}$) is the driving speed, $\eta_m$ is the IWM motorizing efficiency, $\eta_d$ is the battery discharging efficiency, $\eta_i$ is the transmission efficiency from IWM to wheels, $\lambda$ is the inverter efficiency, and $\phi$ is the ratio between the braking and kinetic energies, which is 0.74 for the proposed IWM-AEV. The term “$\phi \cdot \eta_{IWM} \int_{a>0} F_a v dt$” is for the IWM braking recovery energy. If a vehicle starts from a standstill, it must go through an acceleration step before it brakes. Therefore, “$\int_{a>0} F_a v dt$” is the kinetic energy increase of the vehicle before braking, and that is the reason why $a > 0$. When the vehicle is braking, the kinetic energy increase will decrease gradually. 74% ($\phi$) of it will be transferred to the braking energy, which can be recovered. The rest of it will be transferred to unrecoverable energy, such as heat. The braking energy goes to the IWM, and IWM has a braking energy recovery rate $\eta_i$. Through these steps, “$\phi \cdot \eta_{IWM} \int_{a>0} F_a v dt$” is the final IWM braking recovery energy. The relationship between rotating speed, driving speed, and tire rolling radius ($r_d$) gives:

$$n = \frac{v}{2\pi \cdot r_d} \cdot \left( \frac{1000 \text{ m}}{\text{km}} \cdot \frac{1 \text{ h}}{60\text{min}} \right) = \frac{1}{\pi \cdot r_d} \cdot 0.12 \cdot v. \quad (6)$$

In this analysis, a demanding energy factor ($\lambda = T_{\text{dem,1}}/\eta_{m}$) is defined, and the power demand from the traction systems can be written as

$$P_{\text{traction}} = \frac{30}{\pi \cdot r_d \cdot 3.6 \cdot 9550 \cdot \eta_d \cdot \eta_i} \cdot \lambda \quad (7)$$

where the value of the parameters used in (7) is summarized in Table II. The power demand of the traction system is a linear function of the demanding energy factor. As a result, the traction energy consumption per km of the AEV under the upslope driving condition is linearly correlated with the demanding energy factor, which needs to be further analyzed to examine the relationship among energy consumption, slope angle, and driving speed.

Under the upslope driving condition, the slope angle and the length of the slope, and the initial speed are known. Decision variables, objective functions, and constraints can be figured out before carrying out the energy analysis. For the upslope energy-saving control, the decision variable is defined as the vehicle driving speed $v$, and the objective function is the demanding energy factor ($\lambda$), which is given as

$$\lambda = \frac{T_{\text{dem}}}{\eta_m} = \frac{kv^2 + b}{\eta_m} \quad (8)$$

where $k$ and $b$ are constants in the derivation [55], [56], [57], and they can be expanded as follows:

$$F_d = \frac{1}{2} C_d \cdot A \cdot \rho_d \cdot v^2 \quad (9)$$

$$F_v = (m_v + m_c) \cdot g \cdot \cos \theta \cdot f_R \quad (10)$$

$$F_g = (m_v + m_c) \cdot g \cdot \sin \theta \quad (11)$$

$$F_a = (\delta_1 \cdot m_v + m_c) \cdot a_x \quad (12)$$

$$T_{\text{Dem}} = F_{\text{dem}} \cdot r_d = (F_a + F_G + F_R + F_D) \cdot r_d$$

where $\delta_1$ is the vehicle rotating mass conversion factor [56], $m_v$ is the mass of the vehicle, $m_c$ is the mass of the cargo, $a_x$ is the acceleration of the vehicle, $\theta$ is the slope angle, $f_R$ is the road friction coefficient, $C_D$ is the drag coefficient, $A$ is the frontal area, and $\rho_d$ is the air density [57]. Constraints are related to the maximum electric motor rotating speed, torque, and driving conditions. The electric motor’s rotating speed is lower than 1600 rpm based on the data, as shown in Fig. 3. The maximum driving torque that the electric motor can output is 1250 N · m. The working mode is assumed to be constrained by the motoring efficiency map, as shown in Fig. 3(c). IWM-AEV can be optimized to find out the lowest energy consumption point under the specific upslope angle and initial speed using the demanding energy factor.

### D. Downslope Driving Condition

The downslope energy analysis is slightly more complex than the upslope one because braking, coasting down, and energy regenerating need to be taken into consideration. When IWMs are motoring, the calculation is like the upslope circumstance. If the electric motor works in a braking status, the motor works as a generator. The energy regeneration in the EV’s powertain system from the wheels to the battery can be modeled through [54]

$$E_{\text{reg}} = E_{\text{recover}} - E_{\text{SSCM}} = \int P_{\text{recover}} dt - \int P_{\text{SSCM}} dt$$

$$= \int \frac{T_{\text{dem,2}} \ast n \ast \eta_b \ast \eta_c \ast \eta_{\text{recover}} \ast \eta_i \ast \eta_j}{9550} \ast \frac{v dt}{v} - \int P_{\text{SSCM}} dt$$

$$= \phi \eta_{\text{recover}} \int_{a>0} F_a v dt - \frac{1}{\eta_d \eta_i \eta_m} \cdot \left( \int F_d v dt + \int F_v v dt + \int F_g v dt + \int_{a>0} F_a v dt \right)$$

$$- \int P_{\text{SSCM}} dt \quad (16)$$

where $E_{\text{reg}}$ (Wh) is the regenerated energy per km, $P_{\text{recover}}$ (kW) is the energy recovery of the traction system, $\eta_b$ is the IWM braking efficiency, $\eta_c$ is the battery charging efficiency, $\eta_{\text{recover}}$ is the IWM braking energy recovery rate, $T_{\text{dem,2}}$ (N · m) is the torque demand to balance the EV when it is braking, $n$ (rpm) is the rotating speed, and $v$ (km h$^{-1}$) is the driving speed. Defining a parameter called regenerating energy factor ($\lambda_2 = T_{\text{dem,2}}/\eta_b$) and using the relationship of rotating speed and driving speed, as shown in (6), the unit regenerated energy...
is a linear function of the regenerating energy factor

\[ P_{\text{recover}} = \frac{30 \times \eta_c \times \eta_{\text{recover}} \times \eta_f \times \eta_l}{\pi \times r_d \times 3.6 \times 9550} \times \lambda_2 \]  

(17)

where the value of the parameters used in (17) is from Table II. The regenerated energy per km of the AEV under the downslope driving condition is linearly correlated with the regenerating energy factor, which needs to be further analyzed to examine the relationship between regenerated energy, slope angle, and speed.

Under the downslope driving condition, the slope angles, the length of the slope, and the initial speed are given. When the AEV is motoring, the analysis is like the upslope circumstance. When the vehicle is braking, the decision variable is the vehicle’s driving speed \( v \). The objective function is the regenerating energy factor (\( \lambda_2 \)), which yields [55], [56], [57]

\[ \lambda_2 = T_{\text{dem}} \times \eta_b = (kv^2 + b) \times \eta_b \]  

(18)

where \( k \) and \( b \) are given in (14) and (15), respectively. The IWM-AEV can drive at the highest energy regeneration points under real-time downslope angles and speeds based on the regenerating energy factor.

According to the vehicle dynamics and the numerical energy model developed, the energy consumption of the IWM-AEV is influenced by the following conditions: vehicle mass, component efficiencies, vehicle speed, vehicle acceleration, road slope angle, road friction coefficient, and the drag coefficient. The vehicle mass, component efficiencies, and drag coefficient are the built-in parameters of the vehicle. Meanwhile, vehicle speed and vehicle acceleration are variables changing with the driving pattern. Therefore, external conditions are left on the road slope angle and the road friction coefficient. While the road friction coefficient changes with the weather and the road surface materials, it cannot show the advantages of the IWM-AEV configuration, such as the individually controlled motor for a higher motoring efficiency and a higher braking energy recovery rate. As a result, only road slope angle is selected as the significant influencing factor in this study. With the given modeling equations and parameters, the other influencing factors can also be studied with our modeling approach.

### IV. RESULTS AND DISCUSSION

In this section, comparative energy analysis between the baseline EV, AEV without IWM, and the IWM-AEV is conducted for flat road, upslope driving, and downslope driving conditions. By simulating these three EVs, the advantages of the IWM and the autonomous driving technology can be isolated and analyzed specifically. Different combinations of conditions and states for each scenario are listed in Table III. Results of both the baseline EV, AEV without IWM, and the IWM-AEV are acquired from simulation.

#### A. Energy Analysis of the Flat Road Driving

In this study, the energy consumption of the IWM-AEV on the flat road is analyzed under both Urban Dynamometer Driving Schedule (UDDS) and Highway Fuel Economy Test (HWFET) driving cycles to reflect the different energy consumption resulting from different driving patterns. The UDDS and HWFET are standard driving cycles to evaluate the fuel economy of light-duty vehicles mandated by the United States Environmental Protection Agency (EPA). The UDDS represents urban driving, which has more acceleration, deceleration, and stops. Meanwhile, the HWFET represents highway driving, which has less speed fluctuation and a higher average speed. To measure the fuel economy, the test vehicles must follow the given strict speed–time maps. The UDDS lasts 1369 s, and the vehicle needs to travel 7.45 mi with an average speed of 19.59 mph [58]. The HWFET lasts 765 s, and the vehicle needs to travel 10.26 mi with an average speed of 48.3 mph [58]. Based on (5), the unit energy consumption for each driving cycle (\( E_{\text{unit}} \)) can be simulated as [36]

\[
E_{\text{unit}} = \frac{E}{D_{\text{cycle}}} = \frac{E_{\text{traction}} + E_{\text{SSCM}}}{D_{\text{cycle}}} = E_{\text{unit, traction}} + E_{\text{unit, SSCM}}
\]  

(19)

where \( D_{\text{cycle}} \) is the driving distance of each driving cycle.

Coupling IWM efficiency maps and data points in different driving cycles, unit energy consumption for both UDDS and HWFET driving is calculated. The corresponding IWM-AEV unit energy consumptions of UDDS and HWFET under flat road driving are 140.3 and 163.4 Wh km\(^{-1}\), respectively, both around 5% lower than that of the baseline EV, which are at 147.8 and 172.6 Wh km\(^{-1}\), respectively, for the UDDS and HWFET driving. For the UDDS, the traction system and the SSCM consume 94.6% and 5.4% of the total energy. For the HWFET, the traction system and the SSCM consume 98.1% and 1.9% of the total energy. The energy consumption of UDDS driving is lower than that of HWFET because of the braking energy regeneration during local driving. The HWFET driving cycle has a higher average speed, which causes a low SSCM energy consumption on a unit driving distance basis. Although the SSCM system consumes some energy in monitoring and detecting road conditions, the IWM-AEV still has better energy performance than the baseline EV due to its higher energy transmitting efficiency and lower vehicle mass. This result also justifies the advantages of the IWM layout from the energy-saving aspect.
B. Energy Analysis of the Upslope Driving

Since there are no representative driving cycles for upslope driving, our analysis focuses on energy consumption at three typical upslope angles. The energy analysis was carried out on the upslope angles of 5°, 10°, and 15° with a speed range between 0 and 120 km h⁻¹. Under the 5°, 10°, and 15° upslope driving, the optimal upslope speeds with the lowest energy consumption and its energy consumptions of the IWM-AEV are 36 and 538.7, 52 981.7, and 64 km h⁻¹, respectively. The lowest energy consumption points of the AEV without IWM are 564.2 Wh km⁻¹, 1014 Wh km⁻¹, and 1529 Wh km⁻¹ at 34 km h⁻¹, 34 km h⁻¹, and 34 km h⁻¹ for the 5°, 10°, and 15° slopes, respectively. The lowest energy consumption points of the baseline EV are 573.7 Wh km⁻¹, 1065 Wh km⁻¹, and 1568 Wh km⁻¹ at 31 km h⁻¹, 34 km h⁻¹, and 34 km h⁻¹ for the 5°, 10°, and 15° slopes, respectively. Fig. 4 shows the relationship between energy consumption and driving speed for the IWM AEV, the AEV without IWM, and the baseline EV under different upslope angles. It also illustrates the changing motoring efficiency of the IWM at 0~120-km h⁻¹ speed under the upslope driving, which follows the trend of the IWM efficiency contour in Fig. 3.

During upslope driving, a larger slope angle leads to higher energy consumption. For each slope angle, the energy consumption declines first and then rises as the vehicle speed increases. The bounce trend results from the characteristics of the IWM, a type of direct current brushless electric motor, which have a low motoring efficiency when the working torque or speed is close to the boundaries of the efficiency map [59]. The SSCM system will also consume more energy at a low speed due to a longer operating time per unit distance driven. At a high vehicle speed, although the SSCM system consumes less energy, the energy used to overcome the aerodynamic resistance is large. The energy consumption of the SSCM system reflects obviously in the energy curve of the AEV without IWM. Although the level 5 autonomous driving technology helps to reduce energy consumption in the term of motor, the added 240-W SSCM system causes rising energy consumption at low driving speeds. As shown in Fig. 4(a), the IWM-AEV is more energy-efficient than the baseline EV when the driving speeds are higher than 10 km h⁻¹. The IWM-AEV consumes more energy only when the vehicle drives at a low speed (less than 10 km/h) because the IWM motoring efficiency is lowered to a range between 40% and 60% in that driving condition, which is much lower than that of the baseline EV motor (89%) according to the contour map in Fig. 3. As a result, the IWM-AEV is simulated in our analysis under a constant upslope speed, as described above.

C. Energy Analysis of the Downslope Driving

During downslope driving, there could be two states: braking and motoring state. The working state is determined by the relationship between the slope resistance (F_d) and the sum of rolling resistance and aerodynamic resistance (F_r + F_a). The braking state [F_g > (F_r + F_a)], the IWM-AEV drives down along the road, and the IWMs will work as generators to recover energy. Under the motoring state [F_g < (F_r + F_a)], the slope is not steep enough, and the IWM-AEV needs traction forces, which will consume energy. Following another IWM-EV study in literature [60], the initial speed is set at 30 km h⁻¹ to calculate the aerodynamic resistance (F_a) under the downslope driving case. The IWM-AEV in downslope driving is also analyzed for various speeds ranging between 0 and 120 km/h.

1) Braking State: The IWM-AEV will regenerate energy from the braking during the braking state [for this case, F_g > (F_r + F_a)]. With the initial speed set at 30 km h⁻¹ [60], the energy consumption of the IWM-AEV driven on different slope angles (−5°, −10°, and −15°) at a speed ranging between 0 and 120 km h⁻¹ is analyzed. For the −5° downslope driving, the downslope speed of the highest regenerating

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Fig. 4. (a) Energy consumption of the IWM-AEV, and the baseline EV and AEV at 0~120-km h⁻¹ speed under the upslope driving. (b) Motoring efficiency of the IWM at 0~120-km h⁻¹ speed under the upslope driving.
energy is calculated to be 40 km h\(^{-1}\), and the IWM-AEV will regenerate 161.2 Wh km\(^{-1}\) at 40 km h\(^{-1}\). For the \(-10^\circ\) downslope driving, the downslope speed of the highest regenerating energy is calculated to be 54 km h\(^{-1}\), and the IWM-AEV will regenerate 379.6 Wh km\(^{-1}\) at 54 km h\(^{-1}\). For the \(-15^\circ\) downslope driving, the downslope speed of the highest regenerating energy is calculated to be 68 km h\(^{-1}\), and the IWM-AEV will regenerate 585.9 Wh km\(^{-1}\) at 68 km h\(^{-1}\). The highest regenerating energy points of the AEV without IWM are 116 at 63, 281 at 73, and 479 Wh km\(^{-1}\) at 81 km h\(^{-1}\) for the \(-5^\circ\), \(-10^\circ\), and \(-15^\circ\) slopes, respectively. The highest regenerating energy points of the baseline EV are 115 at 59, 274 at 69, and 465 Wh km\(^{-1}\) at 77 km h\(^{-1}\) for the \(-5^\circ\), \(-10^\circ\), and \(-15^\circ\) slopes, respectively.

Fig. 5 shows the relationship between the regenerating energy and slope speed under different downslope angles for the IWM-AEV, the AEV without IWM, and the baseline EV. It also shows the changing braking efficiency of the IWM at \(0\sim120\text{ km h}^{-1}\) speed under the downslope braking. Overall, the IWM-AEV has higher regenerating energy than the baseline EV, up to 26% higher. The regenerating energy increases as the slope angle increases for the same speed, and the speed corresponding to the highest regenerating energy gets larger as the slope angle increases. The regenerating energy factor is directly affected by the slope angle, and it controls the main part of the regenerating energy. For each slope angle, the speed of the highest regenerating energy gets larger when the slope angle becomes larger. The regenerating energy will first increase and then drop as the vehicle speed increases since the IWM braking efficiency is low when the motor works with extremely high or low speed and torque. However, the motor efficiency of the baseline EV in the simulation remains constant, and the drop in its curves is not obvious. When the vehicle speed is too low, the regenerating energy is not capable to overcome the energy needed for SSCM systems. Therefore, the IWM-AEV curves are not started from the axis origin, while the baseline EV curves do since the baseline EV does not have SSCM systems. When the speed is high, the aerodynamic resistance consumes more energy to overcome, resulting in less regenerating energy. In addition, the level 5 autonomous driving technology is beneficial to increase the recovery energy by driving with optimal motor efficiency, and the energy consumption of the SSCM system limits the energy recovery at a low braking speed significantly.

2) Motoring State: The IWM-AEV will work under the motoring state and consume energy to power the vehicle when the slope angle is small. Setting the initial speed at 30 km h\(^{-1}\) [60], the energy analysis on different slope angles \((-0.2^\circ, -0.5^\circ, \text{and} -0.8^\circ\)) with a speed range between 0 and 120 km h\(^{-1}\) was conducted. For the \(-0.2^\circ\) downslope driving, the optimal downslope speed of the lowest energy consumption is calculated to be 31 km h\(^{-1}\), and the IWM-AEV will consume 83.9 Wh km\(^{-1}\) at 31 km h\(^{-1}\) using (16)–(18). For the \(-0.5^\circ\) downslope driving, the optimal downslope speed of the lowest energy consumption is calculated to be 31 km h\(^{-1}\), and the IWM-AEV will consume 49.2 Wh km\(^{-1}\) at 31 km h\(^{-1}\). For the \(-0.8^\circ\) downslope driving, the optimal downslope speed of the lowest energy consumption is calculated to be 31 km h\(^{-1}\), and the IWM-AEV will consume 14.6 Wh km\(^{-1}\) at 31 km h\(^{-1}\). The lowest energy consumption points of the AEV without IWM are 122.4 at 33, 88.2 at 33, and 53.4 Wh km\(^{-1}\) at 31 km h\(^{-1}\) for the \(-0.2^\circ\), \(-0.5^\circ\), and \(-0.8^\circ\) slopes, respectively. The baseline EV demands the lowest energy consumption at 31 km h\(^{-1}\) because the vehicle mass is the main contributor to the energy consumption in this driving condition. The energy consumption is 119, 83.2, and 47.1 Wh km\(^{-1}\) for the \(-0.2^\circ\), \(-0.5^\circ\), and \(-0.8^\circ\) slopes, respectively. Fig. 6(a) shows the relationship between the energy consumption and the driving speed under these downslope angles for the IWM-AEV, the AEV without IWM, and the baseline EV. The motoring efficiency of the IWM at \(0\sim120\text{ km h}^{-1}\) speed under a downslope motoring state is also presented in Fig. 6(b). Similar to the energy curve of the AEV without IWM in an upslope motoring state, the newly
introduced SSCM system raises the unit energy consumption, while the level 5 autonomous driving technology helps to reduce energy consumption. In general, the IWM-AEV consumes much lower energy than the baseline EV due to its lower vehicle mass and higher transmission efficiency at most speeds. However, it is similar to upslope driving that the IWM-AEV consumes more energy when the vehicle speed is less than 10 km/h due to the lowered motoring efficiency. When the slope angle is small and the IWM is working under the motoring state, the energy consumption curve is like that of the upslope condition, and the energy consumption will be smaller than that under the flat road ($0^\circ$) driving condition. A larger slope angle will lead to lower energy consumption in the downslope motoring state. Fig. 6(b) shows that the motoring efficiency fluctuates when the downslope angle is small. This is because the IWM motoring efficiency varies obviously when the driving conditions are close to the boundaries of the motoring efficiency contour.

Based on the simulation, the IWM drive performs better because of the following reasons.

1) The transmission efficiency of the IWM layout is 99% in the simulation, which is higher than that of the baseline FF layout, 93%. The IWM layout has a higher transmission efficiency since the motors are integrated into the wheels. In the baseline FF layout, transmission shafts and a differential are used to connect the electric motor and wheels. The lower transmission efficiency of the baseline FF layout causes energy loss from the motor to the wheels during driving and reduces recovered energy from the wheels to the motor during regenerative braking.

2) By using the IWM layout, the IWM-AEV becomes 45 kg lighter than the baseline EV without transmission shafts and a differential. Therefore, the slope resistance, the acceleration resistance, and the rolling resistance of the IWM-AEV are smaller than those of the baseline EV, with 3.04%, 3.04%, and 2.76%, respectively.

3) IWMs also have a higher motoring efficiency (91% on average) and a higher braking energy recovery rate (85% on average) than the alternating current synchronous electric motor used in baseline EVs (89% and 80% on average). IWMs use brushless permanent magnet electric motor technology, which has the best volume-specific performance among all types of electric motors.

D. Discussion on Simulation Validation

AEV driven by IWM is still a future technology under development and is not commercially available yet. This study is to provide a solid energy consumption study to demonstrate the energy efficiency of this IWM-AEV technology. First, the IWM-AEV modeling approach in this study is based on the simulation of real vehicle operations considering three driving conditions, two standard driving cycles (urban and highway), braking energy recovery, and specific SSCM systems for autonomous driving. Second, all the components and parts configured in the IWM-AEV are commercially available, such as the Nissan Leaf vehicle body, Protean PD-18 IWM, and all the sensors used in the Ford Fusion SSCM systems. These real data and information constructed a validated system for the IWM-AEV by controlling the accuracy and robustness of the simulation from the internal configuration. Besides, our IWM-AEV energy modeling results are reasonable compared to the other studies in the literature on mid-sized EVs or AEVs. For example, the energy intensity of the IWM-AEV in our study for the UDDS driving cycle is 140.3 Wh/km. Meanwhile, the Nissan Leaf EV simulation and the ANL test results on UDDS are 193 and 194 Wh/km, respectively [37]. The energy intensity of a mid-sized AEV for the UDDS driving cycle is 163 Wh/km [41]. In addition, IWM-EVs can save 7.16% of energy under an energy-saving control algorithm in standard driving cycles [62]. These literature results can validate the energy-saving potential of IWM-driven AEV technologies.
E. Case Study

In this case study, the energy consumption of the baseline Nissan Leaf EV was analyzed to demonstrate the energy-saving potential of the configured IWM-AEV technology over conventional EV FF powertrain technology based on an actual test dataset in a driver report [63]. In this case study, a comparison between the baseline EV and its IWM-AEV counterpart has been made under both upslope and downslope driving conditions.

According to this driver report, the baseline Nissan Leaf EV was driven on a round trip from West Los Angeles to Rosamond in the United States [63]. It was driven first upslope for 124.1 km and then downslope for 124.1 km with an average speed of 55 mph (88.5 km h\(^{-1}\)). The slope angle is around 0.30\(^{\circ}\), and the average energy consumption for the whole trip was 157.9 Wh km\(^{-1}\) on the baseline EV, as reported in [63]. To analyze the energy consumption of its IWM-AEV counterpart, the baseline Nissan Leaf is reconfigured to remove the energy consumption from the driver mass, auxiliary systems, and acceleration resistance due to the assumed constant speed driving for the AEV. Based on the parameters in Table II, the energy consumption of the baseline Nissan Leaf EV with a conventional FF powertrain is simulated using the vehicle dynamic equations [see (9)–(15)]. Following our previous analysis method in [41], considering the driver mass as an average American adult bodyweight at 89.7 kg [64], the energy consumption caused by the acceleration resistance, auxiliary systems, and driver mass accounts for 17.3%, 2.7%, and 6.9%, respectively, of the energy consumption of the baseline Nissan Leaf EV. After the three energy consumers are removed, the recalculated average energy consumption is 116.8 Wh km\(^{-1}\) for the whole trip of the baseline Nissan Leaf EV, which can then be used to compare with the energy consumption of the IWM-AEV to benchmark the energy efficiency of the conventional FF powertrain and IWM drivetrain technologies.

The round trip is simulated in two parts for the IWM-AEV. First, the energy consumption of the IWM-AEV under upslope driving at a 0.3\(^{\circ}\) upslope angle is modeled. Using (5)–(8), the optimal upslope speed of the lowest energy consumption is calculated to be 25 km h\(^{-1}\), and under this constant speed, driving the IWM-AEV will consume 109.9 Wh km\(^{-1}\). Second, the energy consumption of the IWM-AEV under downslope driving at a \(-0.3^{\circ}\) downslope angle is modeled. To reflect the continuous driving, the optimal speed with the lowest energy consumption in the upslope simulation (25 km h\(^{-1}\)) is used as the initial speed for the downslope driving. Calculated by (16)–(18), the simulation result shows that the IWM-AEV needs motoring, and the downslope speed corresponding to the minimum energy consumption is 31 km h\(^{-1}\). It will cost the IWM-AEV 82.9 Wh km\(^{-1}\) during the downslope driving. As a result, the average energy consumption of the IWM-AEV during the whole travel is 96.4 Wh km\(^{-1}\). The results show that the energy consumption of the IWM powertrain is 17.5% lower than that of the conventional FF powertrain. According to the eGRID2018 report published in 2020 [65], the electricity GHG emission factor in California is 191.43 g/kWh. Based on California’s average annual travel distance, which is 18 487 km [7], it can save 72.2 kg of CO\(_2\) equivalent of GHG emissions annually by using the IWM-AEV.
As the driving conditions and the GHG emission factors of electricity generation are different from state to state in the U.S., here, we also expanded the GHG analysis to the national level based on the average driving conditions in each state of the U.S., for predictive analysis of the potential benefits of the IWM-AEV at different regions of U.S. Following our previous study on conventional EVs [7], in this analysis, the unit energy consumptions of the IWM-AEV during highway and local driving are separately calculated based on their specific driving conditions in each state and then combined to obtain the GHG emissions with the average travel distance and the emission factor in each state. Specifically, the annual GHG emissions (GHGᵣ) of IWM-AEV at state-level in the United States are calculated as follows:

\[ \text{GHG}_r = (E_{\text{unit, UDDS}} \times T_{r,s,1} + E_{\text{unit, HWFET}} \times T_{r,s,2}) \times D_{a,s} \times U_{G,s} \]

(20)

where \(E_{\text{unit, UDDS}}\) (kWh km⁻¹) is the energy consumption in the UDDS cycle, \(E_{\text{unit, HWFET}}\) (kWh km⁻¹) is the energy consumption in the HWFET cycle, \(T_{r,s,1}\) and \(T_{r,s,2}\) are the local and highway travel ratio in each state [7], \(D_{a,s}\) (km) is the annual travel distance in each state [7], and \(U_{G,s}\) (g/kWh) is the electricity GHG emission factor in each state of the United States (see Table I in the Supplementary Material) [65].

As illustrated in Fig. 7, the annual GHG emissions of the IWM-AEV range from 75.9-kg CO₂ equivalent in Vermont to 2825-kg CO₂ equivalent in West Virginia, while the annual GHG emission saving is between 4.2-kg CO₂ equivalent in Vermont and 155.9-kg CO₂ equivalent in West Virginia (see Tables III and IV in the Supplementary Material). The annual GHG emission saving is mainly determined by the annual travel distance and the electricity GHG emission factor: Although Vermont does not have a significantly short annual travel distance, it has the lowest electricity GHG emission factor (26 g/kWh) compared to the U.S. average electricity GHG emission factor (405.4 g/kWh) [66] since the electricity in Vermont is mainly generated from renewable sources, such as solar, wind, and biodigesters [67]. It developed anaerobic digester systems and set a goal to obtain 75% of its electricity from renewable sources by 2032 [68]. Meanwhile, West Virginia has a high annual travel distance (20 690 km) and a high electricity GHG emission factor (890 g/kWh) due to its highest coal dependency in electricity generation [69]. Overall, the deployment of IWM-AEV technologies can reduce GHG emission by around 5.5% annually from ground transportation, and this study could help facilitate the energy transition of the ground transportation sector in the future.

V. CONCLUSION

Improving energy efficiency and reducing GHG emissions from ground transportation are important for the energy transition of the social economy. In this study, a numerical study was performed on energy consumption and GHG emissions from an IWM-AEV, as a sustainable technology for potential fleet deployment in ground transportation. A bottom-up analysis was conducted to quantify the energy consumption under three driving conditions: flat road, upslope, and downslope. The analysis results show that the IWM-AEV consumes 140.3 Wh km⁻¹ in UDDS and 163.4 Wh km⁻¹ during HWFET driving cycles, respectively, on flat road driving. Simulation results were further compared to baseline EV driving data in West Los Angeles in the case study, and it was found that an IWM-AEV can potentially save 17.5% of energy and 72.2-kg CO₂ equivalent GHG emissions annually during slope driving. The GHG emission analysis indicates that the IWM-AEV can reduce GHG emissions by around 5.5% annually in each state of the U.S. from 4.2- to 155.9-kg CO₂ equivalent. The energy analysis conducted in this study on the IWM-AEV is in line with actual working situations of conventional EVs and IWMs, and thus, it could be useful in supporting the development of future AEV designs and sustainable energy transitions in the ground transportation sector.

Future research should be devoted to the development of actual vehicle tests for different EV models. The advantages of the studied function can be further proven by the comparative road test between typical vehicle models and their IWM-AEV versions. The IWM-AEV comparison analysis will also be more convincing after being validated by the random actual travel data collected from real road conditions.

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