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Energy consumption of electric vehicles in deliveries: effect of dynamic parameters, road profile, load weight and stops

Consumo energético de veículos elétricos em entregas: efeito de parâmetros dinâmicos, perfil da via, carga e paradas

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ABSTRACT
This paper evaluates a physical model for estimating the energy consumption of Battery Electric Vehicles (BEVs) in urban deliveries, as well as proposing an analysis of the impact of speed, road profile, load weight, and number of stops on the range of these vehicles. The proposed microscopic physical model is based on vehicle dynamics equations, considering exponential battery regeneration during braking events. Physical parameters and auxiliary system consumption of the BEV are taken from the literature, and a standard driving cycle is proposed, with a speed and acceleration profile based on real-world data. A total of 160 distinct scenarios were simulated, varying the vehicle's maximum speed, road profile, load weight and number of stops. The results demonstrate that these factors have a significant and quantifiable effect on BEV range. Uphill road grades can reduce range by up to 63% compared to flat terrain, while higher speeds substantially increase energy consumption – range is up to 88% higher at 10 km/h and 54% lower at 80 km/h, compared to a baseline of 40 km/h. Load weight also plays a major role, with a range loss of up to 37% when comparing 1000 kg to 5000 kg loads. Frequent stops further reduce range, with up to a 32% decrease in high stop-density scenarios. These findings highlight the importance of optimizing operational variables when planning BEV-based urban logistics, minimizing the risk of mid-route battery depletion.

RESUMO
Este artigo avalia um modelo físico para estimar o consumo de energia de Veículos Elétricos a Bateria (BEVs) em entregas urbanas, bem como propõe uma análise do impacto da velocidade, perfil da via, peso da carga e número de paradas na autonomia desses veículos. O modelo físico microscópico proposto baseia-se em equações da dinâmica veicular, considerando regeneração exponencial de bateria durante eventos de frenagem. Os parâmetros físicos e o consumo dos sistemas auxiliares do BEV foram obtidos da literatura, e um ciclo de direção padrão é proposto, com um perfil de velocidade e aceleração baseado em dados reais. Um total de 160 cenários distintos foi simulado, variando velocidade máxima, perfil da via, peso da carga e número de paradas. Os resultados demonstram que esses fatores têm efeito significativo e quantificável na autonomia dos BEVs. Inclinações podem reduzir a autonomia em até 63% em comparação a terrenos planos, enquanto maiores velocidades aumentam substancialmente o consumo de energia – a autonomia é até 88% maior a 10 km/h e 54% menor a 80 km/h, em relação à referência de 40 km/h. O peso da carga também desempenha um papel importante, com perda de autonomia de até 37% comparando cargas de 1000 kg e 5000 kg. Paradas frequentes reduzem ainda mais a autonomia, com queda de até 32% em cenários de alta densidade de paradas. Esses achados destacam a importância de otimizar variáveis operacionais no planejamento da logística urbana com BEVs, minimizando o risco de esgotamento da bateria durante o trajeto.

1. INTRODUCTION

The logistics sector plays a critical role in urban development and quality of life due to its economic and environmental impacts (Alarcón, Mac Cawley and Sauma, 2023). Last-mile deliveries have expanded with the rise of e-commerce, which has implications for the sustainability of logistics operations (Anosike et al., 2023). Transport costs make up roughly 6 to 8% of a company's expenses (Ivanov et al., 2021), and the sector is responsible for 24% of energy-related CO2 emissions (Rastani, Yüksel and Çatay, 2019). Freight vehicles, despite representing only 10-15% of vehicle miles in cities, contribute around 33% of traffic-related greenhouse gas (GHG) emissions (Ritchie, 2020; Kin, Hopman and Quak, 2021).

According to Xiao et al. (2021), Electric vehicles (EVs) can lower GHG emissions to roughly 20% of those from fossil fuel-powered vehicles, making them a promising solution for reducing emissions and fossil fuel dependence in urban cargo transport (Pamidimukkala et al., 2024), thereby aiding in the decarbonization of the transport sector (Ruoso and Ribeiro, 2022).

A key incentive for adopting EVs is energy savings. Research shows that EVs save around 35% more energy over their lifecycle compared to internal combustion engine (ICE) vehicles (Zhou, Ou and Zhang, 2013) and reduce costs per kilometer by 60 up to 80% (Tanaka et al., 2014). Electricity consumption for EVs, according to Xiao et al. (2021), can be as low as 10% of the cost required by ICE vehicles. EVs also eliminate fossil fuel use (Rajper and Albrecht, 2020), reducing operational costs and particulate emissions (Ruoso and Ribeiro, 2022), known to have adverse health effects (Lopez and Fernandez, 2020). However, high upfront costs for EVs remain a barrier to widespread adoption (Pamidimukkala et al., 2024).

According to Ruoso and Ribeiro (2022), the market share of EVs remains low, particularly in emerging countries, with only about 10% of the global electric fleet located south of the globe. In Brazil, for example, EVs represented 7% of licensed vehicles in 2024 (ABVE, 2025).

EVs present various challenges across the supply chain, impacting businesses, manufacturers, governments, and investors (Alarcón, Mac Cawley and Sauma, 2023; Anosike et al., 2023), who must adapt strategies to address issues such as high acquisition costs, limited range, slow charging, lack of incentives, and restricted resale markets (Rastani, Yüksel and Çatay, 2019; Ruoso and Ribeiro, 2022; Alarcón, Mac Cawley and Sauma, 2023; Anosike et al., 2023; Pamidimukkala et al., 2024). Psychological barriers, like range anxiety and fear of accidents, also slow adoption, as does a lack of infrastructure and driver training (Viola, 2021). In this sense, many drivers sacrifice comfort to maximize range, using only 50-70% of battery capacity to reduce operational risks (Ullah et al., 2022; Anosike et al., 2023).

Promoting EV adoption involves demonstrating social and environmental responsibility, aligning with ESG goals, and emphasizing benefits like GHG reduction and fossil fuel savings (Viola, 2021; Pamidimukkala et al., 2024). However, public knowledge of EV performance, costs, and maintenance remains limited (Rajper and Albrecht, 2020), indicating a need for education and research to support wider adoption, particularly in markets like Brazil (Castro, Cutaia and Vaccari, 2021*)*.

EVs powered solely by batteries are classified as BEVs and typically have a range of 100-250 km on a full charge (Zhang et al., 2018). In BEV routing literature, most studies assume that energy consumption is constant and linear per unit of distance (Kucukoglu, Dewil and Cattrysse, 2021). However, battery consumption on urban routes depends on more than just distance, as it is significantly influenced by driver behavior, which encompasses speed profiles, acceleration, and braking, as well as road surface conditions, traffic, distance between stops, external temperature, topography, load weight, component efficiency, regenerative braking, usage of auxiliary systems, among others (Basso et al., 2019; Basso, Kulcsár and Sanchez-Diaz, 2021; Anosike et al., 2023; Pang et al., 2024; Snoeck et al., 2024). Consequently, the BEV consumption parameter (kWh/km), obtained by dividing battery capacity (kWh) by maximum range (km), varies considerably across different scenarios (Abdelaty and Mohamed, 2021), making it crucial to study the impact of each factor on energy consumption to minimize the risk of vehicles running out of battery during operation (Basso, Kulcsár and Sanchez-Diaz, 2021).

In this context, a literature review was initially conducted to identify the most significant factors affecting the energy consumption of electric vehicles and to map the main methods for estimating energy consumption in these vehicles. This review supported the primary aim of the paper: to evaluate a physical model based on vehicle dynamics equations to estimate the energy consumption of BEVs, analyzing the impact of selected factors (speed, road gradient, and stop frequency) on vehicle range in last-mile urban delivery operations.

The paper is structured as follows: it begins with a literature review, allowing us to identify the main factors impacting BEV range and the key methods for estimating their energy consumption. Next, based on this review, a physical model based on vehicle dynamics equations with exponential battery regeneration is described to estimate BEV energy consumption. The study then defines the driving cycles considered, as well as the parameters and variation ranges used in the range analyses. The proposed method shows that estimating BEV consumption based solely on distance traveled is subject to operational variations, and that considering additional factors is necessary for a more accurate and reliable range estimate, helping to prevent complete battery depletion during routes.

2. LITERATURE REVIEW

2.1. Parameters that affect the energy consumption of electric vehicles

Energy consumption in EVs is influenced by a variety of parameters and factors, related to both the vehicle's components (mass, frontal area, engine power, drag coefficient, rolling resistance coefficient, battery capacity, battery temperature, state of charge and state of health of the battery) and its dynamics (travel time, distance between stops, average speed, acceleration, and deceleration rates), as well as traffic conditions, driving behavior, and road (gradient, distance traveled, and rolling condition) and environmental conditions (temperature, air density, wind speed, use of auxiliary systems) (Abdelaty and Mohamed, 2021; Basso et al., 2019; Basso, Kulcsár and Sanchez-Diaz, 2021; Chen et al., 2021; Fiori et al., 2021; Kocaarslan et al., 2022; Peña, Dorronsoro and Ruiz, 2024).

Abdelaty and Mohamed (2021) concluded that road grade is the variable that most impacts EV energy consumption, followed by road condition, driving behavior (speed and acceleration profile) and stop density. In the specific scenarios evaluated by the authors, the linear consumption parameter of the BEV (kWh/km) varies substantially, which reveals that energy consumption varies significantly depending on the factors mentioned above. Moreover, Cieslik and Antczak (2023) highlight the effect of the load carried by the BEV on its range, having a significant impact on urban routes.

In terms of driving behavior, Donkers, Yang and Viktorović (2020) developed a study where drivers are categorized as eco-drivers, average drivers, and aggressive drivers, with driving behavior (represented by speed and acceleration profile) shown to significantly impact battery consumption. Aggressive driving at high speeds consumes 17% more energy than economic driving, while at low speeds, such as in urban delivery areas, economical driving uses 5% more energy due to longer travel times. Speed fluctuations, however, affect aggressive drivers more substantially.

In a related study, Abdelaty and Mohamed (2021) classified driver aggressiveness into three levels and found that an increase in one level raises the EV's macroscopic consumption rate by 0.065 kWh/km. The study also highlighted a non-linear relationship between energy consumption and speed, with minor speed changes around 35 km/h, common in urban areas, resulting in notable energy consumption variations.

When it comes to road grade and type, Donkers, Yang and Viktorović (2020) found that energy consumption on urban roads is 20% higher than on expressways. Road grade significantly impacts consumption, with a 1% incline at 30 km/h doubling the energy usage for that section. Additionally, high deceleration elements such as curves, speed bumps, and traffic lights strongly influence consumption, especially for aggressive driving profiles. Similarly, Abdelaty and Mohamed (2021) concluded that a 1% increase in average road grade raises the EV macroscopic consumption parameter by 0.380 kWh/km, potentially reducing the range by up to 35% in extreme cases.

Regarding the transported mass, Cieslik and Antczak (2023) studied the impact of the load carried on the range of light-duty electric vehicles for different types of roads. For highways, the impact of the transported mass is small. However, for urban roads with heavy traffic, the authors recorded a decrease of nearly 14% in the BEV's range when using it fully loaded. This is due to the higher energy consumed in acceleration processes, especially in uphill sections.

Finally, regarding traffic conditions, congestion levels, and the number of stops, these factors have a significant impact on EV energy consumption (Chen et al., 2021). Fetene et al. (2017) incorporated a "rush hour" variable into an energy estimation model to account for periods of heavy congestion, while studies by Li et al. (2016) and Xu and Wang (2018) identified the number of stops per hour as a statistically significant factor in their models. Moreover, Ma et al. (2021) found in a study on electric buses that a route with a high frequency of stops can exhibit energy consumption approximately 30% higher than a route with low stop density.

2.2. Electric vehicle energy expenditure modeling

According to Chen et al. (2021), methods for modeling EV energy consumption can be categorized into rule-based (physical), data-based (statistical), and hybrid models, with Dabčević et al. (2024) identifying a fourth type: elementary models, which relate energy consumption to distance traveled using a macroscopic consumption parameter (kWh/km) similar to manufacturer-provided specifications.

Rule-based methodologies often use Newton's laws to calculate power at the wheels, assuming powertrain efficiency values, as seen in several studies (Basso et al., 2019; Basso, Kulcsár and Sanchez-Diaz, 2021; Fiori et al., 2021; Ding et al., 2022; Kocaarslan et al., 2022; Peña, Dorronsoro and Ruiz, 2024). The physical models use dynamic equations, which make it possible to consider the effect of dynamic parameters, road profile, number of stops, among other factors, on the energy consumption of BEVs. On the other hand, data-based methodologies commonly use machine learning techniques to model relationships between response factors and energy consumption (Modi, Bhattacharya and Basak, 2020; Chen et al., 2021; Maity and Sarkar, 2023).

However, rule-based physical models can be generic, resulting in estimation errors, or excessively complex, which impair their real-time performance (Ye et al., 2016). BEV energy consumption is highly sensitive to internal and external factors, with small variations potentially causing drastic changes in consumption. Due to this variability, deterministic physical models are not always reliable in real-world conditions (Maity and Sarkar, 2023). Conversely, data-based models can suffer from limited predictability and generalization, as they are tailored to the characteristics of specific training datasets (e.g., vehicle properties, routes, or driver behavior). Achieving broad generalization requires diverse datasets, which are difficult to obtain due to the scarcity of well-structured data from electric fleets (Dabčević et al., 2024). Hybrid approaches, therefore, aim to combine the strengths of both methodologies, reducing the prediction errors and improving performance (Ye et al., 2016; Ullah et al., 2022).

Table 1 presents a summary of the papers reviewed in sections 2.1 and 2.2. The following acronyms must be defined: Physical Model (PM), Empirical (E), Hybrid Model (HM), Data-Based Models (DBM), Simulation (S), Simulation and Experiments (SE), GPS Data (GPSD), Collected Data (CD), Trapezoidal Speed Profile (TrSP), Machine Learning (ML), Typical Speed Profiles (TySP), Exponential Battery Regeneration (EBR), Linear Battery Regeneration (LBR), Non-Linear Battery Regeneration (NLBR), Empirical Equations (EE), Constant Consumption (CC), Basic Auxiliary Systems (BAS).

Table 1: Summary table – reviewed papers

Source	Model type	Data used	Speed profile	Battery regeneration	Auxiliary systems
Wang et al. (2015)	PM, E	S	TrSP	NLBR, EE	-
Wang et al. (2017a)	PM, E	SE	SE	NLBR, EE	CC
Wang et al. (2017b)	HM	GPSD	GPSD	-	BAS
Wang et al. (2017c)	HM	GPSD	GPSD	-	BAS
Cauwer et al. (2017)	HM	GPSD	ML	-	-
Genikomsakis and Mitrentsis (2017)	PM	S	TySP	LBR	S
Fiori and Marzano (2018)	HM	GPSD	GPSD	NLBR, EBR	CC
Donkers et al. (2020)	HM	SE	S	LBR	BAS
Modi et al. (2020)	HM	S	S	LBR	CC
Lopez and Fernández (2020)	HM	S	S	LBR	-
Chen et al. (2021)	HM	GPSD	GPSD	-	-
Fiori et al. (2021)	HM	GPSD	GPSD	NLBR, EBR	BAS
Basso et al. (2021)	PM	S, GPSD	TySP, GPSD	LBR	CC
Abdelaty and Mohamed (2021)	HM	S, DC	S	NLBR, S	BAS
Ullah et al. (2022)	DBM	GPSD	GPSD	-	CC
Ding et al. (2022)	PM	GPSD	TySP	-	-
Kocaarslan et al. (2022)	PM	S	TySP	LBR	S
Li et al. (2022)	HM	GPSD	GPSD	-	BAS
Maity and Sarkar (2023)	DBM	GPSD	GPSD	-	-
Pena et al. (2024)	PM	GPSD	GPSD	NLBR, EBR	CC
Dabčević et al. (2024)	HM	GPSD	GPSD	NLBR	CC
Snoeck et al. (2024)	DBM	DC	GPSD	-	-

In this sense, considering the exposed limitations, a physical model is selected for this study. To advance with a hybrid model and develop machine learning models that integrate physical estimates with additional predictive variables, real operational data would be required to extract factors — data that is difficult to obtain at scale. Therefore, this study evaluates the ability of a physical model to estimate BEV range under various scenarios, as will be described in the methodology section, since this type of model is able to capture the effect of speed, acceleration, road profile, load weight, number of stops, among other factors, on the energy consumption pattern of BEVs.

3. METHODOLOGY

3.1. Physical model for estimating the energy expenditure of BEVs

A microscopic physical model for point-to-point energy consumption estimation was employed (Peña, Dorronsoro and Ruiz, 2024). The model assumes that the total energy consumption of the BEV, on all segments i of a route ($i = 1,2,\ldots,n$), is composed of three main components: traction energy ($E_{traction}$), divided by the BEV's overall efficiency (η_{global}); energy for the operation of auxiliary systems (E_{aux}); and regenerative braking energy (E_{regen}), multiplied by the efficiency of the BEV's regenerative system (η_{regen}). The total energy consumption (E_{total}) can be seen on Equation (1).

$$E_{total} = \frac{\sum_{i=1}^{n}\left(E_{traction,i}\right)}{\eta_{global}} + E_{aux} - \eta_{Regen}\sum_{i=1}^{n}\left(E_{Regen,i}\right) \tag{1}$$

According to George and Sivraj (2021), auxiliary systems in BEVs can increase energy consumption up to 45%, depending on usage, with a 30% increase considered in this study to account for the continuous operation of main systems like power steering, lights, and power windows. Then, the total energy consumption (E_{total}), defined in Equation (1), can be rewritten in Equation (2) as the sum of energy required for vehicle movement across route segments ($E_{traction,i}$), adjusted by the BEV's overall efficiency (η_{global}) and by the auxiliary consumption factor ($\gamma_{aux} = 1.3$), and reduced by the regenerative braking energy (E_{regen}) multiplied by the efficiency of the BEV's regenerative system (η_{regen}).

$$E_{total} = \frac{\gamma_{aux}}{\eta_{global}}\sum_{i=1}^{n}\left(E_{traction,i}\right) - \eta_{Regen}\sum_{i=1}^{n}\left(E_{Regen,i}\right) \tag{2}$$

The overall efficiency of the BEV (η_{global}), in Equation (2), considers the efficiencies of the motor (η_{motor}), battery (η_{bat}), transmission system (η_{transm}), and converters (η_{conv}) (Donkers, Yang and Viktorović, 2020). The equation for overall efficiency is described in Equation (3).

$$\eta_{global} = \eta_{motor} \times \eta_{bat} \times \eta_{transm} \times \eta_{conv} \tag{3}$$

Battery regeneration occurs during deceleration and braking, where the EV's kinetic energy is partially converted into electricity (Chen et al., 2021). To model regenerative braking, some studies use linear regeneration mechanisms (Donkers, Yang and Viktorović, 2020; Fiori et al., 2021; Kocaarslan et al., 2022), while others prefer exponential models (Fiori and Marzano, 2018; Peña, Dorronsoro and Ruiz, 2024). While the linear model depends on the driver's efficiency, which is based on literature but lacks operational validation, the exponential model is preferable as it relies on the EV's speed profile during the route, making it more predictable. Therefore, Equation (2) can be rewritten as shown in Equation (4), considering that the energy regenerated through braking is modeled exponentially ($E_{RegenExp}$). The efficiency of exponential regenerative braking on segment i ($\eta_{RegenExp,i}$) is given by Equation (5). It depends on the global efficiency of the BEV (η_{global}) and on the regenerative braking factor ($f_{RegenExp,i}$), which is influenced by the vehicle's speed in that specific segment (v_i).

$$E_{total} = \frac{\gamma_{aux}}{\eta_{global}} \sum_{i=1}^{n} \left(E_{traction,i} \right) - \sum_{i=1}^{n} \left(E_{RegenExp,i} \times \eta_{RegenExp,i} \right) \tag{4}$$

$$\eta_{RegenExp,i} = f_{RegenExp,i} \times \eta_{global} = \left[1 - e^{-v_i(t)} \right] \times \eta_{global} \tag{5}$$

The traction energy in segment i ($E_{traction,i}$) is defined in Equation (6) as the sum of positive kinetic energy ($E^{+}_{kinetic,i}$), positive gravitational potential energy ($E^{+}_{gravit,i}$), air drag energy ($E_{airgrad,i}$), and rolling resistance energy ($E_{rolling,i}$) in that segment.

$$E_{traction,i} = E^{+}_{kinetic,i} + E^{+}_{gravit,i} + E_{airdrag,i} + E_{rolling,i} \tag{6}$$

The traction force in segment i ($F_{traction,i}$), defined in Equation (7), is the sum of the positive acceleration force ($F^{+}_{acc,i}$), Equation (8), air drag force ($F_{airdrag,i}$), Equation (9), positive gravitational force ($F^{+}_{gravit,i}$), Equation (10), and rolling resistance force ($F_{rolling,i}$), Equation (11), in that segment. Here, m_i is the total vehicle mass (kg) in segment i; $a_i(t)$ is the vehicle acceleration $(\mathrm{m/s^2})$ in segment i; $v_i(t)$ is the vehicle speed $(\mathrm{m/s})$ in segment i; ρ_{air} is the air density $(\mathrm{kg/m^3})$; f_{ad} is the aerodynamic drag coefficient (dimensionless); A_{fr} is the vehicle frontal area $(\mathrm{m^2})$; g is the acceleration due to gravity $(\mathrm{m/s^2})$; $f_r(v)$ is the rolling resistance coefficient (dimensionless); and θ_i is the road gradient in segment i.

$$F_{traction,i} = F^{+}_{acc,i} + F_{airdrag,i} + F^{+}_{gravit,i} + F_{rolling,i} \tag{7}$$

$$F^{+}_{acc,i} = m_i \, a_i^{+}(t) \tag{8}$$

$$F_{airdrag,i} = \frac{1}{2} \rho_{air} \, f_{ad} \, A_{fr} \, v_i^2(t) \tag{9}$$

$$F^{+}_{gravit,i} = m_i \, g \, sin\left(\theta_i^{+} \right) \tag{10}$$

$$F_{rolling,i} = m_i \, gcos(\theta) \, f_r(v_i) \tag{11}$$

The traction power in segment i ($P_{traction,i}$) is given by the sum of the forces ($F_{traction,i}$) multiplied by the EV's speed at the end of segment i, $v_i(t)$, as shown in Equation (12). If $a_i(t)$ of the segment is negative, the corresponding force component associated with acceleration is not considered, as this component will be associated with regenerative braking.

$$P_{traction,i} = \left(F^{+}_{acc,i} + F_{airdrag,i} + F^{+}_{gravit,i} + F_{rolling,i} \right) \times v_i(t) \tag{12}$$

Finally, the components $E_{kinetic}$, E_{gravit}, $E_{airdrag}$ and $E_{rolling}$ are defined by their respective powers multiplied by the time interval (Δt_i) spent to traverse segment i, as shown in Equations (13), (14), (15) and (16), respectively. Substituting these equations into Equation (6) fully defines the $E_{traction,i}$ component. Lastly, the exponentially regenerated energy portion on segment i ($E_{RegenExp,i}$) is simply the negative kinetic energy ($E^{-}_{kinetic,i}$), as defined in Equation (17).

$$E_{kinetic,i} = \begin{cases} E^{+}_{kinetic} = F^{+}_{acc,i} \times v_i(t) \times \Delta t_i, a_i(t) \geq 0 \\ E^{-}_{kinetic} = F^{-}_{acc,i} \times v_i(t) \times \Delta t_i, a_i(t) < 0 \end{cases} \tag{13}$$

$$E_{gravit,i} = \begin{cases} E^{+}_{gravit} = F^{+}_{gravit,i} \times v_i(t) \times \Delta t_i, \theta_i(t) \geq 0 \\ E^{-}_{gravit} = 0, \theta_i(t) < 0 \end{cases} \tag{14}$$

$$E_{airdrag,i} = F_{airdrag,i} \times v_i(t) \times \Delta t_i \tag{15}$$

$$E_{rolling,i} = F_{rolling,i} \times v_i(t) \times \Delta t_i \tag{16}$$

$$E_{RegenExp,i} = E^{-}_{kinetic,i} \tag{17}$$

3.2. Driving cycle

Based on the speed profiles proposed by Basso, Kulcsár and Sanchez-Diaz (2021) and Ding et al. (2022), a trapezoidal speed profile is used as the base driving cycle, as shown in Figure 1.

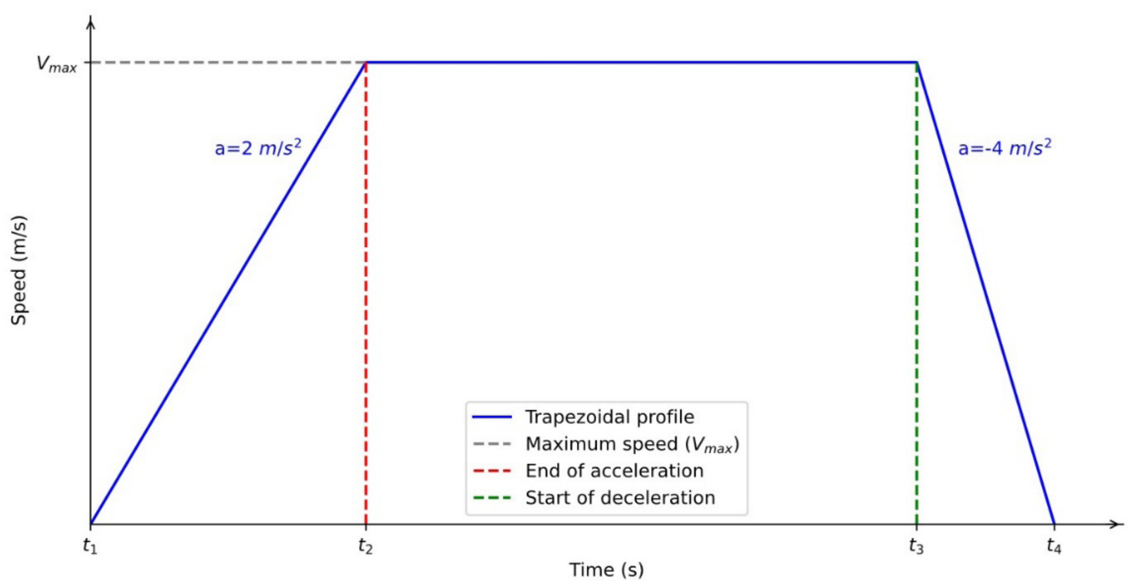

Figure 1. Speed profile. [Adapted from Basso, Kulcsár and Sanchez-Diaz, 2021, and Ding et al., 2022].

The driving cycle is divided in four points: the vehicle starts from rest and accelerates at a constant rate of 2 m/s^2 (Zhang et al., 2023) until reaching the maximum speed of the road at point 2; The vehicle maintains this speed until reaching point 3; The vehicle begins to decelerate at a constant rate of 4 m/s^2 (Donkers, Yang and Viktorović, 2020) until reaching rest again at point 4. This base driving cycle is repeated n times throughout the proposed scenarios, where n depends on the number of stops established in the respective scenario.

3.3. Parameters and variation ranges considered in the analysis

The BEV's technical specifications and other relevant parameters used by the physical model proposed on Section 3.1 are listed in Table 2.

Table 2: Truck technical specifications and considered parameters

Attribute	Value	Unit	Source
Curb weight (T)	6380	kg	Volkswagen (2021)
Battery capacity	105	kWh	Volkswagen (2021)
Frontal area (A_{fr})	4.45	m^2	Volkswagen (2021)
Rolling resistance (f_r)	*	-	Donkers, Yang and Viktorović (2020)
Acceleration due to gravity (g)	9.81	m/s^2	Fiori et al. (2021)
Drag coefficient (f_{ad})	0.7	-	Fiori et al. (2021)
Air density (ρ_{air})	1.225	kg/m^3	Fiori et al. (2021)
Motor efficiency (η_{motor})	95%	-	Peña, Dorronsoro and Ruiz (2024)
Battery efficiency (η_{bat})	97%	-	Peña, Dorronsoro and Ruiz (2024)
Transmission efficiency (η_{transm})	96%	-	Peña, Dorronsoro and Ruiz (2024)
Converter efficiency (η_{conv})	90%	-	Peña, Dorronsoro and Ruiz (2024)
Regenerative System Efficiency ($\eta_{RegenExp,i}$)	*	-	Peña, Dorronsoro and Ruiz (2024)
Regenerative Braking Factor ($f_{RegenExp,i}$)	*	-	Peña, Dorronsoro and Ruiz (2024)
Auxiliary Systems Consumption (γ_{aux})	1.3	-	George and Sivraj (2021)

*These attributes do not have a constant value, as they depend on other parameters. Their equations were defined in Section 3.1.

The following scenarios were proposed to represent urban environments: maximum speeds (v_{max}) of 10, 20, 30, 40, 50, 60, 70, and 80 km/h, covering typical speeds observed on expressways, arterial roads, collector roads, and local streets; constant road grades (θ) of -3%, -1.5%, 0%, 1.5%, and 3%; load weight of 1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500 and 5000 kg; and Distances Between Stops (DBS) of 500 m, 1000 m, 2000 m, and no stops (i.e., the vehicle travels at a constant free flow).

The analysis was divided into two parts. First, the mass carried by the BEV is considered constant throughout the entire operation cycle. For this constant mass, which corresponds to 40% of the vehicle's total net weight, we combined the different parameters described, resulting in 160 distinct scenarios to assess the BEV's range. The second analysis aims to explore the impact of the transported mass on the BEV's range. To conduct this analysis, typical speed limit ranges were selected: fast traffic (80 km/h), arterial roads (60 km/h), collector roads (40 km/h), and local roads (30 km/h). For each speed limit range, a range surface (km) is generated, relating to the load carried (kg) and the road incline (%). The analyses were divided into two sets to allow for three-dimensional visualization, as this paper explores the impact of four different variables on the range of BEVs.

For conducting the parametric analyses and obtaining the results, Python (v. 3.12) was used along with the libraries Pandas (v. 2.2.2), NumPy (v. 1.26.4), and Matplotlib (v. 3.8.4). A methodological flowchart is presented in Figure 2, outlining the step-by-step process followed to obtain the results presented in Section 4.

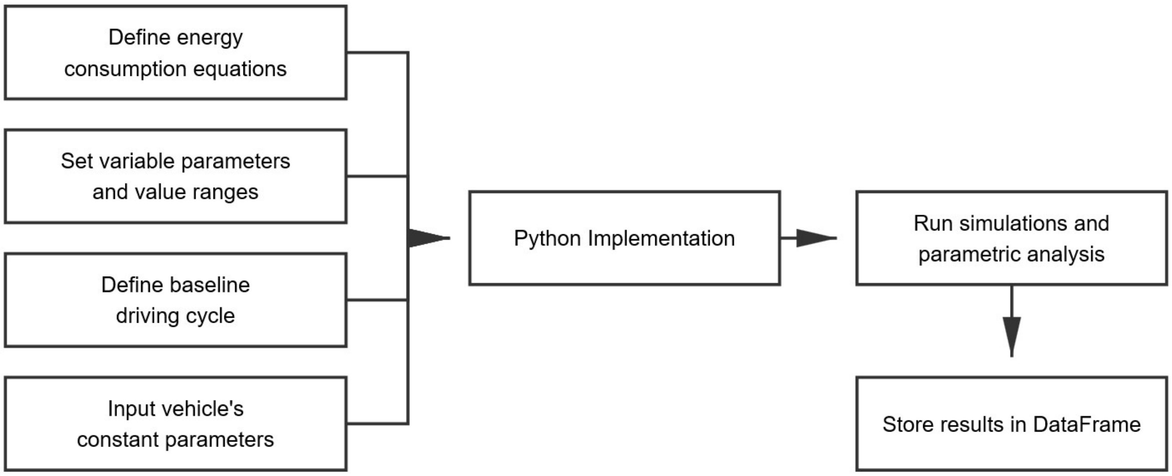

Figure 2. Methodological flowchart.

4. RESULTS

Based on the energy model proposed in Section 3.1, the driving cycle outlined in Section 3.2, and the scenarios described in Section 3.3, two analyses were conducted.

First, Table 3 presents the range in kilometers (km) for each scenario of maximum speed (km/h), road grade (%), and distance between stops (DBS, in meters). This scenario considers a load of 2500 kg, which represents 40% of the BEV's net weight.

Table 3: Range of the BEV (km) for each proposed scenario; the vehicle payload is constant

	Road grade (%)																			
DBS (m)	**No stops**					**2000 m**					**1000 m**					**500 m**				
Speed (km/h)	**-3**	**-1.5**	**0**	**1.5**	**3**	**-3**	**-1.5**	**0**	**1.5**	**3**	**-3**	**-1.5**	**0**	**1.5**	**3**	**-3**	**-1.5**	**0**	**1.5**	**3**
10	248	248	248	76	45	239	239	239	76	45	231	230	230	75	45	216	215	215	73	44
20	227	227	227	75	45	200	200	200	71	44	178	178	178	68	42	146	146	146	63	40
30	204	203	203	72	44	160	159	159	65	41	131	131	131	60	39	96	96	96	51	35
40	180	180	180	69	42	126	125	125	59	38	96	96	96	51	35	65	65	65	41	30
50	158	158	158	65	41	99	99	99	52	35	72	72	72	43	31	46	46	46	32	25
60	138	138	138	61	39	79	79	79	46	32	55	55	55	36	27	34	34	34	26	21
70	120	120	120	57	38	64	64	64	40	29	43	43	43	31	24	26	26	26	21	17
80	105	105	105	53	36	52	52	52	35	27	34	34	34	26	21	20	20	20	17	14

Next, Figure 3 presents the range surfaces (km) for different speed limits (km/h), considering the variation in road grade (%) and transported load (kg). It is important to note that these scenarios assume a flat road surface and no stops on the driving cycle.

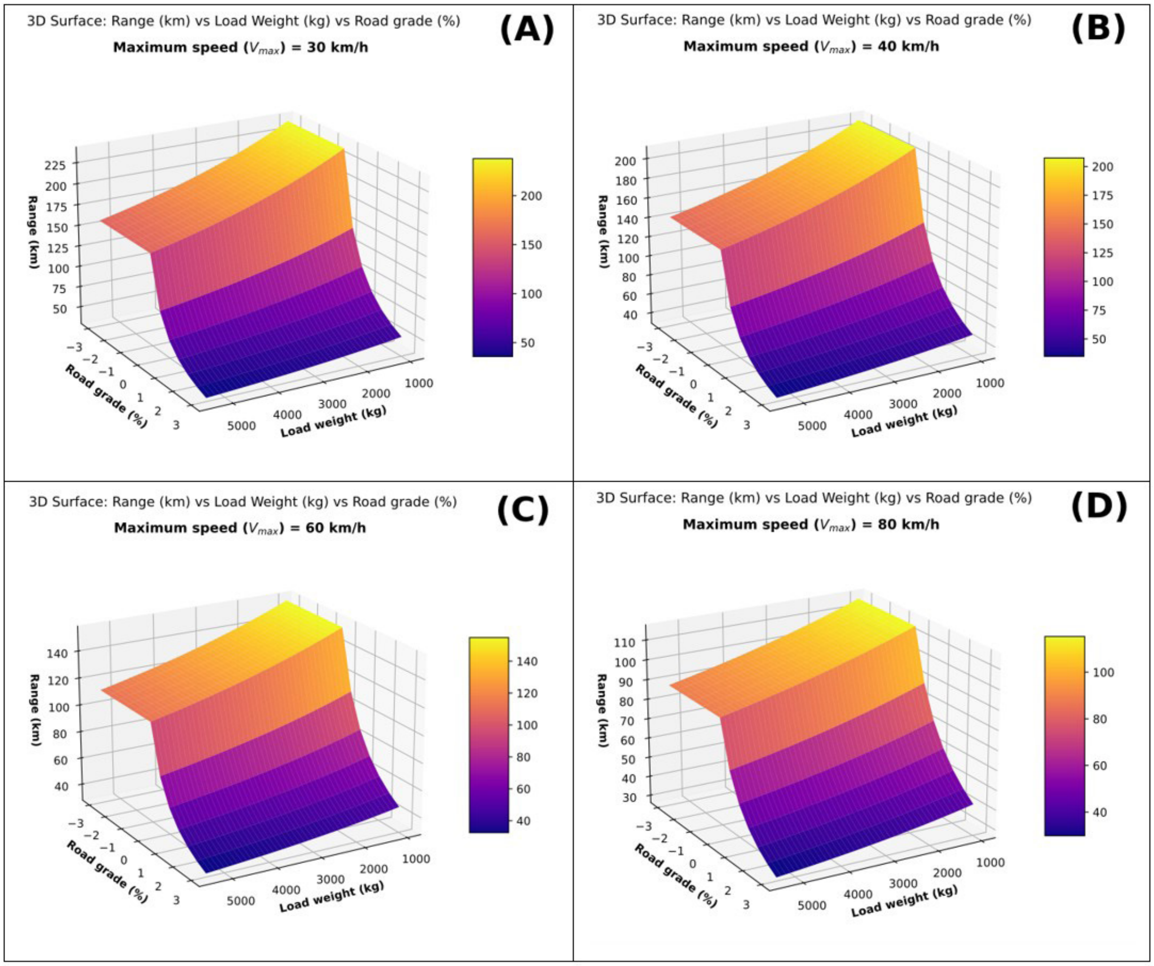

Figure 3. Range surfaces (km) for A) 30 km/h; B) 40 km/h; C) 60 km/h; and D) 80 km/h.

The reference BEV used in this study, according to the vehicle's user manual (Volkswagen, 2021) provided by the manufacturer, has a range of 110 km. It is assumed that the test scenario used by the BEV manufacturer consists of a flat terrain with no stops and an empty vehicle (i.e., the total mass equals the curb weight). This assumption is made as the specific test conditions for the manufacturer's range estimates are not publicly disclosed. It is important to note that the results in Table 3 consider the total mass of the BEV as the sum of the curb weight and a load of 2500 kg, resulting in an approximate 40% increase in mass compared to the empty vehicle.

Analyzing Table 3, it is observed that for all speed ranges and stop intervals, the BEV's range remains approximately constant across downhill scenarios as well as on flat terrain. This behavior is expected because the energy expenditure was estimated using vehicle dynamics equations, and in downhill segments, the BEV does not consume battery power for the gravitational potential energy component. Furthermore, given that acceleration and deceleration rates are constant, and the speed profile is trapezoidal, the vehicle does not utilize the downhill slope to reduce acceleration rates, which could otherwise decrease battery usage for the kinetic energy component.

For uphill segments, however, as shown in Table 3, the BEV's range is significantly impacted across all speed profiles. For a constant grade of 1.5%, the BEV's range is, on average, 48% lower compared to the baseline flat terrain scenario. At a constant grade of 3%, the range decreases even further, with an average reduction of 63%. It is worth noting that the reduction in range is not linear with varying speed ranges, being more pronounced at lower speeds. This is due to the characteristics of the physical estimation model, where scenarios with lower speeds have longer time horizons and therefore higher power consumption for the gravitational potential energy component, which dominates in uphill cases.

Moreover, using the 40 km/h speed range as a reference to analyze the impact of speed on range, it is noted that for adjacent speed ranges of 30 km/h and 50 km/h, the variation in range is less significant (an increase of 24% and a decrease of 18%, respectively). For lower speed ranges, such as 10 km/h and 20 km/h, there is a substantial increase in range (88% and 54%, respectively). Conversely, for higher speed ranges, such as 70 km/h and 80 km/h, the reduction in range is considerable (-42% and -54%, respectively). Again, the impact of maximum speed on range is not linear, being more pronounced at lower speeds, resulting in significantly higher range for low-speed segments.

In addition, for the proposed physical model, more frequent stops generate additional acceleration moments, increasing battery consumption for the kinetic energy component. This is evident in Table 3 across all speed ranges, with the reduction in range becoming more pronounced at higher speeds. In a baseline scenario with no stops, lower speeds (10 to 40 km/h) exhibit an average range reduction of 13% for stops every 2000 m, 21% for stops every 1000 m, and 32% for stops every 500 m. On the other hand, higher speeds (50 to 80 km/h) show an average range reduction of 36% for stops every 2000 m, 52% for stops every 1000 m, and 68% for stops every 500 m.

Now, analyzing the range surfaces in Figure 3, it is clear that the transported mass has a significant impact on the range of BEVs. For the local road speed range (Figure 3A, 30 km/h), for both downhill and flat scenarios, the ranges fall between 157 and 239 km, being up to about 52% greater when comparing the case where the BEV is loaded with 5000 kg to the case where the BEV is loaded with 1000 kg. The behavior is similar for the other speed ranges. For the maximum speed of collector roads (Figure 3B, 40 km/h), the range falls between 142 and 209 km. For the maximum speed of arterial roads (Figure 3C, 60 km/h), the range falls between 112 and 155 km. Finally, for the maximum speed of fast roads (Figure 3D, 80 km/h), the range falls between 88 and 116 km. The greatest disparity between ranges is found in the lower speed ranges, which can be explained by the increased time required to move a larger load, resulting in more power needed, as estimated by the physical model.

For 3% uphill scenarios, for the local road speed range (Figure 3A, 30 km/h), the ranges fall between 33 and 52 km, which are up to about 58% greater when comparing the case where the BEV is loaded with 5000 kg to the case where the BEV is loaded with 1000 kg. For the maximum speed of collector roads (Figure 3B, 40 km/h), the range falls between 32 and 51 km. For the maximum speed of arterial roads (Figure 3C, 60 km/h), the range falls between 30 and 47 km. Finally, for the maximum speed of fast roads (Figure 3D, 80 km/h), the range falls between 28 and 42 km. The greatest disparity between ranges, again, is found in the lower speed ranges. In the uphill scenario, however, the significant impact of the transported load on the BEV's range is highlighted, explained by the fact that mass directly affects the kinetic energy, gravitational potential, and friction with the road surface. When comparing the most extreme case (maximum incline with the highest speed) with the mildest case (downhill and lower speed), the range, for an average load within the considered range, can be up to 82% lower, from 198 km to 35 km.

5. CONCLUSIONS

Electric vehicles, while presenting a significant opportunity for decarbonizing last-mile logistics operations, face several challenges, principally the uncertainty surrounding their range. In practice, logistics operators often rely on macroscopic consumption parameters (kWh/km) as a reference for routing, typically provided by the manufacturer as a maximum range with a full battery. However, the literature demonstrates that energy consumption by BEVs varies significantly depending on several factors, including driving behavior (speeds, accelerations, and braking), road surface conditions, traffic, stop spacing, ambient temperature, topography, payload, vehicle component efficiency, and the use of auxiliary systems. Therefore, it is essential to better understand the impact of these factors on BEV consumption to optimize logistics operations, maximizing their range while minimizing the risk of battery depletion mid-route.

In this context, this study provided a literature review to identify the key factors influencing EV energy consumption and to map the main methodologies used in the literature to estimate energy consumption for these vehicles. Building on this theoretical foundation, the study proposed a physical model based on vehicle dynamics equations to estimate the energy consumption of BEVs. The impact of speed variation, road grade, load weight and number of stops on vehicle range in urban delivery operations was analyzed. The results show that range, measured in kilometers, varies significantly with changes in the parameters under study.

The impact of downhill grades on range is negligible; however, uphill grades substantially reduce BEV range compared to flat terrain, with up to a 63% range loss for a constant 3% incline. Similarly, speed strongly influences energy consumption. For a baseline speed of 40 km/h, range can be up to 88% greater when speed is reduced to 10 km/h or 54% lower when increased to 80 km/h. Moreover, the transported mass significantly impacts energy consumption, resulting in a range loss of up to 37% (comparing a load of 1000 kg and 5000 kg for the most unfavorable scenario of maximum incline and low speeds). Finally, stop frequency also significantly impacts range, especially in high-frequency stop scenarios typical of urban environments, with up to a 32% reduction in range for stops every 500 meters compared to a no-stop scenario.

The quantitative results obtained indicate that the impacts on vehicle range resulting from variations in individual parameters are consistent with values reported in the literature, despite differences in the methodologies employed for range estimation. In this study, rather than relying on commercial simulation software, a simulation was developed based on a microscopic physical consumption model grounded in rigid body dynamics equations. This modeling approach allows for parametric analysis by systematically varying both the model's input parameters and the operating conditions.

The results are limited by the consideration of constant road grades in the scenarios. Therefore, future work should explore mixed topography profiles in the scenarios and evaluate the impact of varying the vehicle's payload along the route. Furthermore, future research could also assess the impact of the various other parameters mentioned in the literature review, conducting isolated or combined analyses of these factors.

AUTHORS' CONTRIBUTIONS

AD: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; JPGC: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization; HTYY: Conceptualization, Funding acquisition, Project administration, Resources, Supervision.

CONFLICTS OF INTEREST STATEMENT

The authors declare that there is no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE-ASSISTED TECHNOLOGY

The authors declare that artificial intelligence tools (ChatGPT and DeepL) were used only for language translation and editing purposes. The authors reviewed and edited the final manuscript and assume full responsibility for its content.

DATA AVAILABILITY STATEMENT

The data supporting the results of this study are not publicly available because they are proprietary data belonging to a Brazilian beverage and food distribution company. The data were provided to researchers at the Center for Innovation in Logistics Systems at the University of São Paulo as part of a partnership between the company and the research laboratory but cannot be publicly disclosed. The Python models and scripts can be made available upon request to the corresponding author.

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