A Method for Determining Optimal Electric Range by Considering Electric Vehicle Lightweighting on Perceived Ownership Cost

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Abstract

The limited driving range due to high costs and low energy densities of batteries constrains the battery electric vehicle (BEV) market growth. Lightweighting in theory can reduce energy consumption rate and extend the driving range. The knowledge gap is to quantitatively link the cost-effectiveness of light-weight technologies with range extension and consumer acceptance of BEVs. In this study, a physics-based energy consumption model of BEVs is constructed and associated with a statistics-based model on the basis of travel surveys. A perceived cost of ownership (PCO) is then developed by adding intangible costs to traditional total cost of ownership models. We estimate, at the disaggregate vehicle model and driver level and the aggregate market level, 1) the extended range due to lightweighting for a given battery size; and 2) the optimal electric range based on lightweighting decisions. The cost-effectiveness of lightweighting for BEV range extension is found to vary with income-dependent daily range limitation value, driving patterns and lightweighting technology costs. In general, adopting lightweighting in BEVs is more cost-effective for consumers with higher daily limitation value, as well as for those with higher driving intensity or suitable daily driving patterns. When the lightweighting involves a higher vehicle production cost, less lightweighting could reduce the overall PCO for BEV owners. 4 of the selected top ten BEV models are found to benefit from additional 2.09%-4.45% lightweighting. The method built in this study can guide automakers in planning R&D investments in battery and lightweighting technologies.

Keywords: Battery electric Vehicle, Battery size, Cost of vehicle ownership, Electric driving range, Light-weighting, Optimization

1. Introduction

The battery electric vehicle (BEV) has been one of the major alternative fuel vehicle technologies. According to the International Energy Agency, in 2021, the sales of plug-in electric vehicles (BEVs and plug-in hybrid electric vehicles) in the light-duty segment have reached over 6.6 million, nearly 9% of the global light-duty vehicle market (Paoli and Gül, 2022). The cumulative registrations of plug-in electric vehicles have also been over 0.7 million in the U.S. by the end of 2021 (Paoli and Gül, 2022). The society has generated a culture starting to value electric vehicles as a future purchase option (Jin and Slowik, 2017), and suitable business models are invented to promote the convenience of electric vehicle uses (Secinaro et al., 2020).

The BEV with clean electricity is also regarded as one of the effective alternatives to decarbonize the transportation sector. The transportation sector has been one of the major carbon emitting sectors in the U.S.: it produced over 29% of greenhouse gas (GHG) emissions in 2019 (U.S. EPA, 2020). The Biden administration pledged to reach net-zero GHG emissions no later than 2050 and set a goal of reducing GHG emissions by 50–52% compared to 2005 levels by 2030 (White House, 2021a). To meet the target, it is expected that a large investment will be into the low- or zero-carbon technologies in all industries. Therefore, a strategic transitioning of light-duty vehicles from conventional internal combustion engine vehicles (ICEVs) to BEVs or other alternative fuel vehicles has been a consensus in the U.S. and the world.

However, due to expensive production cost and limited energy density of battery, the electric driving range still constrains the large-scale acceptance of BEVs. BEVs with a longer electric range are still expensive high-end products, while BEVs with a shorter electric range are unable to meet all the travel demands of general drivers. Several approaches, summarized in Table 1, have been developed to address this BEV range anxiety problem. By comparing the pros and the cons of these major approaches, we can find that most approaches require long-term investments with uncertain returns, such as R&D efforts in hope for battery technology breakthroughs. It is impossible to ameliorate the electric range or battery issue in a short period, even though these pathways could effectively improve the electric range or permanently solve the battery problem. One exception is the vehicle optimal design approach, which aims at optimizing vehicle components to maximize value proposition to consumers. Mechalek et al. proposes using quantitative tools and methods to optimize product designs based on cost factors and consumer attributes in order to maximize product success in the market (Michalek et al., 2011). If resulting in cost-effective strategies, the vehicle optimal design approach can achieve market impacts as soon as a vehicle design cycle.

Table 1. Major Approaches on Solving the Electric Range Problem in BEVs.

Approaches	Type	References	Pros	Cons
Vehicle optimal design	Component system design	Autonomie, a tool by Argonne, is adopted for vehicle system energy and cost analysis (Kim et al., 2013).	Small investment. Quick return.	Limited improvement.
Battery technology improvement	New battery materials or design.	Developing new li-ion battery electrolytes (Xu, 2021).	Solving the electric range problem permanently.	Massive investment. Long R&D time period.
	Battery swapping technology	Vallera et al. believes the battery swapping technology could reduce grid impacts (Vallera et al., 2021)	Shorten the charging time. Reduce the driver's range anxiety.	Massive investment. Difficult to standardize technology
Infrastructure	Charging network	The Biden Administration plans to provide $5 billion to build a national charging network (White House, 2021b).	Reduce the driver's range anxiety.	Massive investment. Hard to benefit EVs in rural areas.
	Charging technology: fast charging, extreme fast charging(xFC), & wireless charging	Domínguez-Navarro et al. designed a fast-charging station (Domínguez-Navarro et al., 2019). Zeng et al. optimized control to improve wireless charging efficiency (Zeng et al., 2021).		Expensive installations. Potential battery lifetime damage.
Consumer awareness education	Consumer behavior	BEV consumer awareness activities can foster growth of the market and understanding how to better implement (Jahangir et al., 2019; Jin and Slowik, 2017; Secinaro et al., 2022).	Cultivate BEV culture and help the public to understand the limitations.	Unclear benefit-cost balance.
Government support	Policy and incentives	Ou et al. 2018 quantifies that the vehicle policies can bring extra BEVs to market (Ou et al., 2018).	Financially compensate for the range anxiety.	Massive investment. Unclear benefit-cost balance.

Vehicle optimal design involves many aspects such as compatibility and consistency among physical-subsystems (Kim et al., 2013), market or consumer-oriented design (Michalek et al., 2011), and optimization under policy constraints (e.g., fuel-saving technology integration to meet the fuel economy regulations (Shiau et al., 2009)). As the literature review shows, light-weighting could impact electricity consumption rates and extend electric range, but has not been considered in the BEV range optimization. Therefore, this study creates a method to optimize the design of electric range in BEVs by comprehensively considering vehicle dynamic features and performance, more specifically, the fuel consumption rate impacts from the light-weighting technologies and materials in vehicles. Called Perceived Cost of Ownership (PCO), this method adds optimization and intangible costs such as range anxiety and charging inconvenience to the traditional total costs of ownership (Burnham et al., 2021), which usually only consider out-of-pocket or tangible costs. The PCO model developed in this study can help stakeholders from industry and government agencies to understand the value and strategies of diversifying optimal BEV ranges for accelerating vehicle electrification, and the role of light-weighting technologies in BEV range optimization.

The organization of this paper is as shown as below. Section 1 provides research background on the BEV market/technology developments and obstacles, and presents objectives and motivations. Section 2 briefly introduces the major literature review and data collections on light weighting and cost of ownership in the BEVs. Section 3 describes the analysis methods and scenario designs. Section 4 presents scenario analyses and gives the optimized options through benefit-cost analysis. The final section summarizes the conclusions and the future work.

2. Literature Review

2.1. Weight impact on vehicle energy consumption

Lightweighting has been a promising approach to meet with more stringent governmental regulatory requirements on fuel efficiency and environmental legislations on harmful emission. Vehicles with lightweighting reduce the required propulsive energy and may lead to further weight reduction through powertrain downsizing without sacrificing dynamic performance. Prevailing approaches for reducing vehicle weight include substitution of low-density materials, advanced manufacturing technologies (additive manufacturing, laser welding, High-pressure die casting, etc.), and optimal structural designs (size, shape, topology optimization, etc.). A study on the historic trend of vehicle weight, fuel efficiency, material compositions, and GHG emission was conducted for American and Japanese cars in the past thirty years (Kawajiri et al., 2020). After investigating the life-cycle analysis on the material substitutions using advanced high-strength steel (AHSS), aluminum alloy, carbon fiber reinforced polymer, and magnesium alloy, it was concluded that the AHSS remains the most promising for reducing GHG emissions with respect to material substitutions and lightweighting design.

The physics-based relationship between vehicle weight and mass-dependent fuel consumption had been formulated based on vehicle dynamics theories with parameters including rolling, rotating, and acceleration loads (Kim et al., 2015; Kim and Wallington, 2016). The effects of powertrain resizing on the fuel reduction values (FRVs) was studied and compared with the mass-induced fuel consumptions without down-resizing powertrains (Kim and Wallington, 2016). Del Pero et al., focusing on gasoline turbocharged cars, concluded that the FRVs will be improved by downsizing the powertrain after primary weight reduction to maintain vehicle performance specified in the preliminary design stage (Del Pero et al., 2017). Similar physics-based models were applied to analyze the energy demand (in MJ/100km) of ICEVs (Geyer and Malen, 2020a) and BEVs (Geyer and Malen, 2020b) by calculating the force required at the driving wheels and the corresponding torque and rotating velocity transmitted through powertrain. Variations of the energy demand were plotted as functions of changes in three vehicle characteristics (mass, frontal area and rolling resistance) in a range of 40% reduction to 40% addition with an increment of 10%. Geyer and Malen found that energy demand is most sensitive to vehicle mass in the New European Driving Cycle (NEDC) (Geyer and Malen, 2020a). It was concluded that the change in vehicle energy demands due to mass reduction (MJ per 100 km driven and per 100 kg reduction) are smaller for BEVs with efficient powertrains (Geyer and Malen, 2020b).

Compared to the conventional version of ICEVs, a vehicle with considering lightweighting can clearly reduce the vehicle's overall lifecycle energy consumption and emissions (Kelly and Dai, 2021). Similar conclusions were achieved by others. A 10% reduction in vehicle mass will produce an approximately 6-7% reduction in fuel consumption for passenger cars and 4-5% reduction for light-duty trucks (National Research Council, 2015). Actually, because of energy consumption saving, the lightweighting version of BEV is also expected to have a longer driving distance comparably (Kelly and Dai, 2021). Therefore, the industry believes lightweighting remains a crucial approach for lowering fuel consumption (ICEVs) and improving driving distance (BEVs) (Bailo et al., 2020). The simulation models by Argonne National Laboratory predicted the potential weight of various vehicle classes (compact car, midsize car, small SUV, midsize SUV, and pick-up) will be reduced by 10-24% in MY 2045 (Islam et al., 2020).

2.2. Lightweighting in battery electric vehicles

The BEVs are projected to increase by more than 60% globally in the next two decades (Applied Value Group, 2021). By 2040, the automakers will offer only carbon-neutral products and most governments will issue policies and legislations to eliminate ICEVs (Applied Value Group, 2021). Combined with vehicle lightweighting, increasing energy efficiency through electrified powertrains and other technical advancements help reduce GHG emission (Luk et al., 2017). Specifically, present BEVs are heavier than similar ICEVs due to the batteries, sensors, and infotainment systems, and are restricted to short-distance commutes only. Combined with large improvements in battery technologies, lightweighting plays a crucial role to push BEV range to beyond 700 miles and support long range travel (Applied Value Group, 2021). Therefore, the lightweighting is important for the development of BEVs.

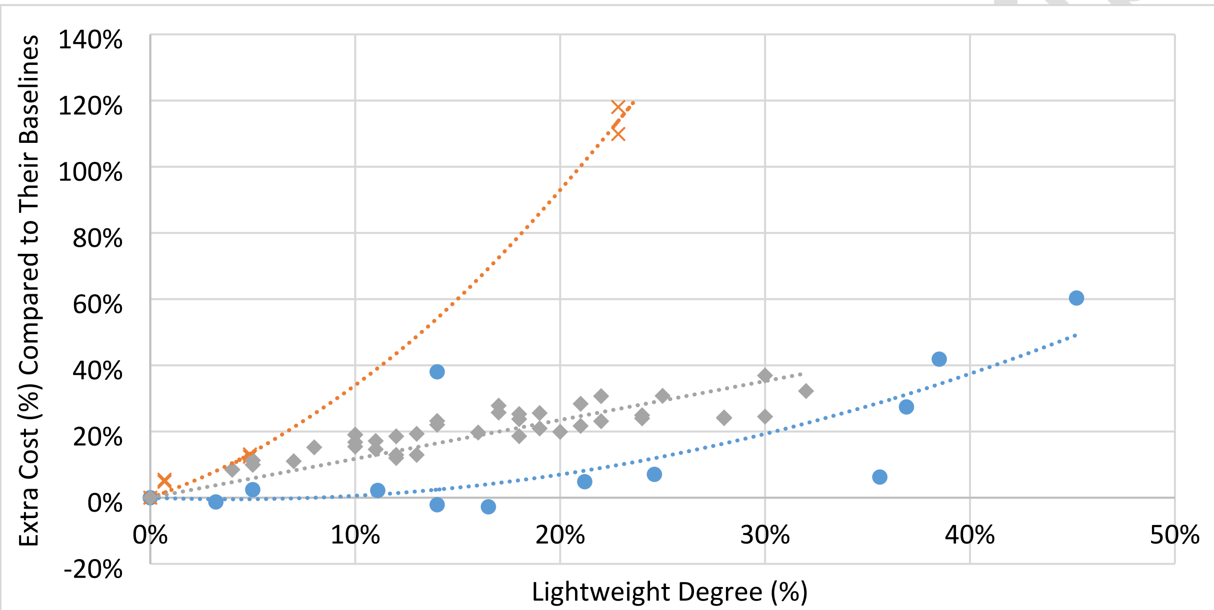
Substituting materials for body-in-white and substituting materials for the powertrain system, especially battery and motor/generator, play an equally critical role in the cost management related to the BEV's lightweight design. Thus, full vehicle cost trade-offs under different material substitution decisions and battery technology improvement scenarios should be studied at the same time. For example, Burd et. al. compared the weight reductions from material substitution with Advanced High-Strength Steel (AHSS) and aluminum alloys in their applications for lightweight design of BEV bodies and closures (Burd et al., 2021). Corresponding mass scaling costs of the battery, motor and chassis subsystems were calculated and compared for the lightweight designs with AHSS and aluminum. It is found that although replacing carbon steel with AHSS will reduce the manufacturing and assembly costs, the aluminum version of vehicle body and closure will help reduce the vehicle weight further and has advantage on battery and motor cost. So, the substituting materials for body-in-white method is still the main pathway for BEV's lightweighting and is considered by this study.

For BEVs, the computer simulations based analysis for the structural stiffness, durability, dynamic behavior and crashworthiness are often performed (Del Pero et al., 2020). In the study of Del Pero et al., the computer simulations were conducted for energy consumptions of 10 different BEVs with different technical features (mass, motor power, and power-to-weight ratio). The simulations result of energy consumption for BEVs were expressed as functions of car masses and are applied to calculate the Energy Reduction Value (ERV) coefficient (kWh/ (100 km × 100 kg). Impact Reduction Value (IRV) coefficients, the product of ERV and GWP (the Global Warming Potential factor), were calculated for assessing the environmental impact of lightweight design of BEVs (Del Pero et al., 2020). This study uses the similar logic to evaluate the lightweighting degree of different BEV models.

2.3. Optimizing cost of ownership by considering lightweighting and electric range

Cost of ownership is adopted as an objective function to quantify the light weighting impacts on the BEV's electric range optimization. Therefore, there are two components in the objective function: cost related to BEV electric range; and vehicle lightweighting cost. Current cost of ownership mostly focuses on tangible cost components such as vehicle purchase price and fuel cost and rarely considers intangible costs due to limited driving range and refueling inconvenience. Intangible costs related to the vehicle range typically are not considered by cost of ownership analysis until the range becomes much more expensive, for example, in the cases of BEVs or fuel cell vehicles (FCVs). The combination of limited range and limited recharging/refueling availability translates to the range limitation cost and recharging/refueling inconvenience cost, which are intangible but have been measured by attempts. Consideration of such two intangible costs in the total cost of ownership analysis exists, but rarely. Lin is one of pioneers who quantified the intangible costs impacted by the electric range and battery system (Lin, 2014). Lin segmented the impacted PCO by three components: battery cost, range limitation cost, and energy (electricity) cost for driving the BEV (Lin, 2014). Hao et al. developed a Monte Carlo based model for vehicle ownership cost analysis by integrating the electric range optimization with consumer heterogeneity (Hao et al., 2020). With considering the cost and benefit analysis, Shi et al developed a physics-based model to investigate the relationship between the energy consumption reduction and lightweight rate (Shi et al., 2019). It illustrates that the lightweighting clearly helps reduce BEV energy consumption and battery capacity needed for achieving the same driving range. However, Shi et al. also admitted that the potential extra cost from the lightweighting technologies could offset the benefits from the energy saving. Therefore, a feasible optimization of this relationship is needed.

Lightweighted vehicle means less energy consumed under the same conditions and an improvement of driving range of electric vehicles, however the lightweighting also costs much and varies by substituted materials. This study summarized the lightweighting degree (%) with the extra cost (%) from three different publications into Figure 1 (Bailo et al., 2020; Islam et al., 2020; Mascarin et al., 2015). The lightweighting degree (%) means the vehicle weight saving (%) after using the substitute materials for the baseline vehicles. For example, if the weight of a baseline vehicle is 2000 kg and the weight saving is 400 kg after using lightweighting technology, then the lightweighting degree is 20%. The extra cost means the extra cost for implementing the lightweighting technology. For example, if the production cost of baseline vehicle is $ 20,000, the cost with the lightweighting technology is $4000, then the extra cost would be 20%. One important note, the baseline vehicles from these three references are totally different. In Mascarin et al.'s work, the baseline vehicle is the 2013 Ford Fusion vehicle model (Mascarin et al., 2015). In Islam et al.' work, the baseline vehicle is an average vehicle for different vehicle types in 2015, such as small car, mid-size car, small SUV and mid-size SUV, respectively (Islam et al., 2020). In Bailo et al.'s work, the baseline vehicle is an average vehicle for different vehicle types in 2020, respectively (Bailo et al., 2020). More details of the relations between lightweighting degree and extra cost are presented in Appendix A-C. Since Macarin et al. gives abundant information on the lightweighting, this study uses the fitting curve and baseline vehicle proposed by Macarin et al (Mascarin et al., 2015). According to the literature review based on the previous studies, this study combinedly associates the PCO on the electric vehicles with the lightweighting cost, so as to create a method to improve the electric range of BEVs or lower BEV's battery size.



*Each publication has different baseline (0%), which determines their trends of relative extra cost.

Figure 1. The relations between lightweighting degree and extra cost revealed by publications (Bailo et al., 2020; Islam et al., 2020; Mascarin et al., 2015).

3. Methodology

3.1. Optimization model

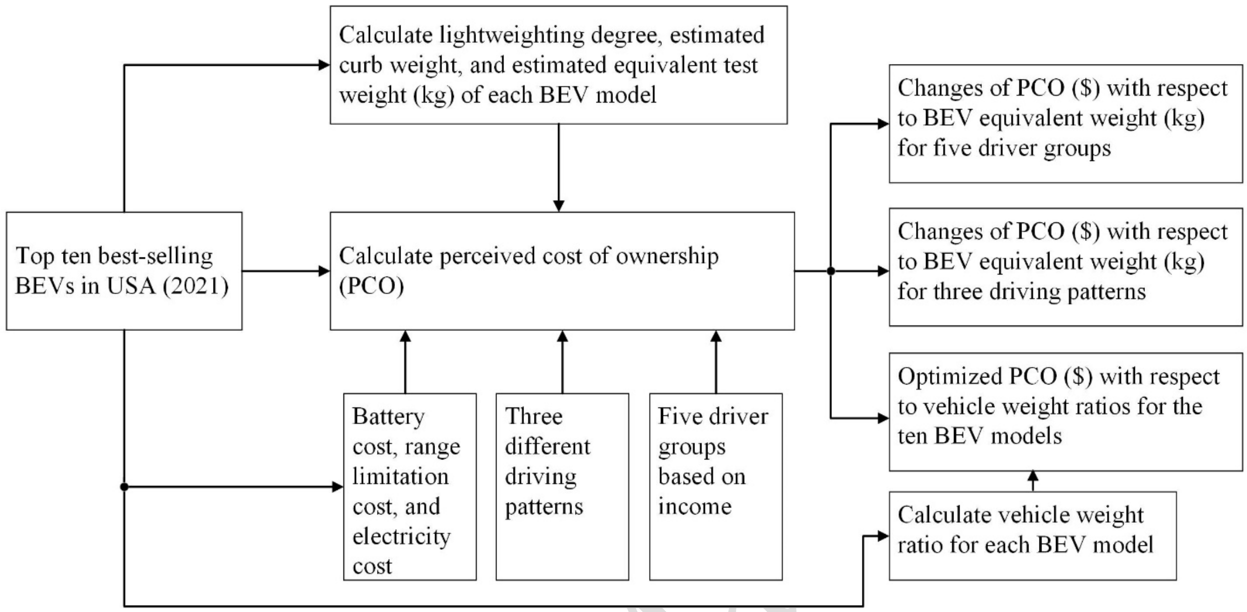


Figure 2. Flowchart for the PCO optimization model with consideration of lightweight and BEV driving range.

The analysis flow in this study is described by Figure 2. The critical component is the physics-based energy consumption model of electric vehicles which is associated with the statistics modeling of the U.S. driving patterns. The physical-based energy consumption relationship between vehicle mass and vehicle energy consumption without/with powertrain resize has been derived by Kim et al. 2016 (Kim and Wallington, 2016). Accordingly, the mass-dependent fuel consumption $F_w(M)$ for BEVs formulated as Eqn. (1) (Kim and Wallington, 2016).

$$F_w(M_t) = \frac{1}{H_f \eta_c \eta_t} \int \left(Av + Bv^2 + (1 - \emptyset\mu)avM_t\right)dt \tag{1}$$

where H_f, η_c, and η_t are the heating value of fuel, energy conversion efficiency, and transmission efficiency. $\emptyset$ is the ratio of braking to kinetic energy, and μ is the regenerative braking efficiency. A and B are coast-down coefficients, which are referred to the U.S. Environmental Protection Agency (EPA) for each vehicle model (U.S. Environmental Protection

Agency (EPA), 2022). v and a are vehicle speed, and acceleration, respectively. M_t is the vehicle equivalent test weight (kg). Accordingly, the energy consumption rate by vehicle mass, FRV (L/100km·100kg) for a specific vehicle model with an equivalent test weight at m_0 (kg), is shown in Eqn. (2) (Kim and Wallington, 2016).

$$FRV = \frac{dF_C(M_t)}{dM_t}|_{M_t=m_0} = \left(\frac{F_w|_{M_t=m_0}}{F_w|_{M_t=m_0} + F_x + F_F}\right)\left(\frac{F_C|_{M_t=m_0}}{\varphi}\right) \quad (2)$$

where, for a specific vehicle model weighting at m_0, F_x (L) is the mass-independent fuel consumption. F_F (L) is the miscellaneous energy loss which is adjusted to zero by calibrating the power demand from accessories (such as heating, ventilation, and air conditioning; electronics) in BEVs. F_C is the energy consumption rate (kWh/km, or gasoline equivalent liter per kilometer, L_{GE}/km), which is obtained from the U.S. EPA (U.S. Environmental Protection Agency (EPA), 2022) and is associated with the vehicle weight, m (kg). φ is the unit conversion factor.

Therefore, FRV is the first-order differential equation of F_C with respect to vehicle equivalent test weight—M_t. Based on this relationship, it can be deduced that, when FRV is a positive value, reducing the vehicle weight leads to a lower energy consumption rate. The lighter vehicle weight has two unique benefits for BEVs – either extending the electric range or reducing the battery capacity or both. Considering the extra weight burden from the battery system, such benefits can be much more significant than fuel-saving benefits from reducing the weight of conventional gasoline vehicles.

On the other hand, the optimization of electric range based on the U.S. travel patterns has been explored by Lin (Lin, 2014), as shown in Eqn. (3).

$$C_{BEV}(r) = C_b(r) + C_l(r) + C_e(r) \quad (3)$$

Where, C_{BEV} is the total PCO of vehicle impacted by battery cost (C_b), range limitation cost (C_l) and energy (electricity) cost (C_e) for driving the BEV. r is the electric range. All the three cost components are associated with the electric range.

More specifically, the battery cost $C_b(r)$ ($) is conducted by Eqn. (4).

$$C_B(r) = \frac{r}{r_0} \cdot S_0 \cdot B \cdot \sigma \tag{4}$$

Where, r_0 is the electric range (mile) of the baseline, S_0 is the battery size of the baseline (kWh), B is the battery cost ($/kWh), which is believed to reach $132/kWh in 2021 (Henze, 2021). σ is the price markup factor, which is assumed to be 1.2 (Lin, 2014). The electric range, r, is assumed to be linearly correlated with the battery size, B_s (kWh), as shown in Eqn. (5). Accordingly, when the battery size is fixed, the energy consumption rate, F_C (kWh/km, or gasoline equivalent liter per kilometer, L_{GE}/km) will be inversely related to the electric range.

$$r = \frac{B_s}{F_C(M)} \tag{5}$$

The range limitation cost $C_l(r)$ ($) is calculated by Eqn. (6).

$$C_l(r) = L_0 \int_{r_d}^{X_m} p(x)dx + L_1 \int_{r_d}^{X_m} xp(x)dx \tag{6}$$

Where, x is the random daily vehicle miles traveled (VMT, mile) that follows a probability density function $p(x)$; X_m is the maximum daily VMT (miles); r_d is the range limited per day (miles); L_0 and L_1 are the hypothetical fixed and variable range limitation costs ($ and $/mile, respectively) that occur as if all days during the vehicle's lifetime are served by the backup vehicle for one mile per day. The probability density function follows the gamma distribution, which is common to describe the distribution of the daily driving patterns of the drivers (Greene, 1985). The average daily VMT in the U.S. – 29.2 miles (Bureau of Transportation Statistics, 2017), and the daily commute distance 14 miles (StreeLightData, 2018) are used for obtaining the gamma distribution (Lin, 2014). The characteristics of the driving patterns and vehicle use are given by Table 2.

Table 2. Major Features of Driving Patterns and Vehicle Use.

Feature	**Value**	**Source**
Driving - Mode (miles)	14.00	(StreeLightData, 2018)
Driving - Mean (miles)	29.20	(Bureau of Transportation Statistics, 2017)
Gamma - Shape Parameter	1.92	Calculated based on driving mode/mean
Gamma - Scale Parameter	15.20	Calculated based on driving mode/mean
Vehicle Lifetime (Years)	10	Assumption
Discount Rate	7%	(Congressional Research Service, 2016)
Lifetime Mileage (mi)	74857	Calculated based on lifetime and discount
Daily Range limitation Value for BEV (L_0)	$151	(Lin, 2014)

The electricity cost $C_e(r)$ ($) is calculated by Eqn. (7).

$$C_e(r) = \frac{L_e(r)}{L} \cdot VMT_l \cdot P_e \quad (7)$$

Where, $L_e(r)$ is the average daily vehicle miles traveled with electricity (VMT, mile) that follows a probability density function $p(x)$; L is the average daily VMT in the U.S. (Bureau of Transportation Statistics, 2017); VMT_l is the discounted lifetime VMT (miles), which is based on the assumption of 10 years vehicle lifetime and 7% discount rate; P_e is the electricity price – $0.148/kWh in 2021 (Texas Power, 2021).

In summary, this study builds on and expands Eqn. (1-7) to derive the physical-based relationship among vehicle weight (kg), battery size (kWh), and electric range (miles) with consideration of intangible electric vehicle usage cost, light weighting manufacturing cost and lifetime impacts, as shown in Eqn. (8). T is the comprehensive PCO with considering the extra cost brought from the vehicle weight changes $\Delta C_w(M_t)$, comparing to it from the original vehicle model; and extra intangible electric vehicle usage cost $\Delta C_{BEV}(M_t)$, compared to it from the original vehicle model. The optimization will be the minimization of the summed PCO.

$$min\ (T) = min\ (\Delta C_w(M_t) + \Delta C_{BEV}(M_t)) \quad (8)$$

3.2. Lightweighting evaluation

To quantify and compare the impacts of BEV weight on the PCO (T), this study selects the ten best-selling BEV models in the U.S. in 2021. The study collects the vehicle performance features from the U.S. EPA (U.S. Environmental Protection Agency (EPA), 2022), the FuelEconomy.gov (fueleconomy.gov, 2020), and public vehicle information websites (White, 2022). The vehicle performance for these vehicle models is shown in Appendix D.

Different vehicle models are probably produced with various lightweighting materials; therefore, there should be a baseline to measure their lightweighting degree. This study uses the 2013 Ford Fusion vehicle model, used by Mascarin et al. (Mascarin et al., 2015), as the baseline of lightweighting degree. It means the lightweighting degree of the 2013 Ford Fusion is 0% relative to other vehicle models in this study. In addition, as the battery system takes a heavy part of the BEVs, the overall curb weight of a BEV could be larger than the same model with an internal combustion engine. Thus, the lightweighting degree discussed in this study refers to curb weight for the vehicle non-powertrain part – M_{np} (kg). The curb weight (M_c, kg) for the 2013 Ford Fusion is 1554 kg, and powertrain part is 454 kg (Mascarin et al., 2015). Thus, the non-powertrain part is 1100 kg.

The quantified measurement index is the weight non-powertrain part per unit volume (kg/m^3). The vehicle volume is calculated by Eqn. (9).

$$V = fp \cdot h \tag{9}$$

Where, V is the vehicle volume (m^3) which is used for quantifying the lightweighting degree. fp is the vehicle footprint (m^2), and h is the vehicle height (m). These values are pulled from the database for FuelEconomy.gov (fueleconomy.gov, 2020).

The weight analysis of electrified powertrain (M_p) of BEVs are segmented into three parts: battery system M_{pb}, motor system M_{pm}, and other part M_{po}. The weight of battery is associated with the battery energy density (δ, kWh/kg). The power sources of all the BEV models in this study adopt the lithium-ion batteries, which are capable of providing up to 0.25-0.27 kWh/kg for commercialized use (Persun, 2021). Considering other affiliations in the battery system, this study uses 0.17 kWh/kg for the battery system. The motor weight is associated with the motor power (P_m, kW), this study assumes the power density (ε, kW/kg) is 1.216 kW/kg, an estimate from the Tesla Model S features (Teslarati, 2013). In addition, the weight (M_{po}) for other parts is assumed to be 306 kg, an estimate from the Tesla Model S features (Teslarati, 2013). The calculation is shown in Eqn. (10).

$$M_p = \delta \cdot B_s + \varepsilon \cdot P_m + M_{po} \tag{10}$$

Therefore, the weight of vehicle non-powertrain part per unit volume (ρ_{np}, kg/m^3) is calculated by Eqn. (11).

$$\rho_{np} = \frac{M_{np}}{V} = \frac{M_c - M_p}{V} \tag{11}$$

Where, M_{np} is the vehicle non-powertrain weight (kg), and M_c is the vehicle curb weight (kg). And the lightweighting degree is obtained by Eqn. (11).

$$d_i = \frac{\rho_{np,i} - \rho_{np,B}}{\rho_{np,B}} \tag{12}$$

Where, d_i is the relative vehicle lightweighting degree of vehicle i compared to the baseline – 2013 Ford Fusion. $\rho_{np,i}$ is the weight of vehicle i's non-powertrain part per unit volume (kg/m^3). $\rho_{np,B}$ is the weight of baseline vehicle's (2013 Ford Fusion) non-powertrain part per unit volume (kg/m^3). Figure 3 presents the relative vehicle lightweighting degree (d_i) of the top ten best-selling BEVs in the U.S. The positive percentage value indicates the vehicle's non-powertrain part has a better lightweighting performance than the non-powertrain part of the baseline vehicle – 2013 Ford Fusion; and the negative percentage value indicates a worse performance. Figure 3 shows only two vehicle models have a worse performance, and these two are both luxury cars. The weight information for calculating the relative lightweighting degree is given by Appendix E. Based on the relative lightweighting degree information, this study is able to calculate the extra cost or saving on lightweighting.

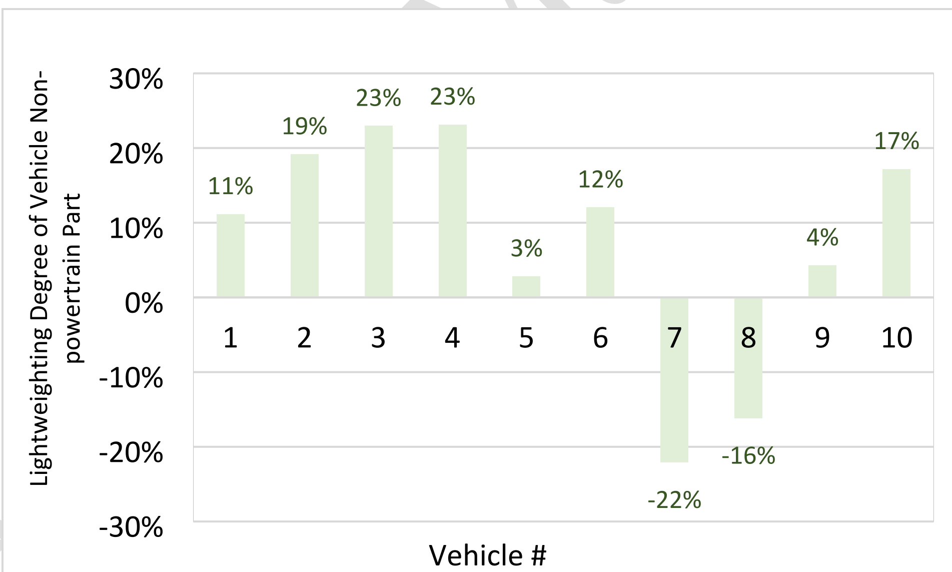


Figure 3. The lightweighting degree of vehicle non-powertrain part for the 2021 ten best-selling BEVs in the U.S.

Based on the lightweighting degrees of vehicle non-powertrain part calculated by Eqn. (12) and the powertrain weight obtained by Eqn. (10), we can estimate the curb weights for each BEV models when their lightweighting degrees are the same as they are for the baseline vehicle – 2013 Ford Fusion, i.e., the lightweighting degree is 0%. The calculation is shown in Eqn. (13).

$$M_{c0\%,\,i} = \frac{M_{c,i} - M_{np,i}}{1 - MAX(0, d_i)} + M_{p,i} \tag{13}$$

Where, $M_{c0\%,\,i}$ is the estimated curb weight (kg) of BEV model i when its lightweighting degree is 0%. $M_{c,i}$ is the curb weight (kg) of BEV model i, which is given by Appendix D. $M_{np,i}$ is the non-powertrain part weight (kg) of BEV model i. $M_{p,i}$ is the powertrain part weight (kg) of BEV model i. d_i is the lightweighting degree of the non-powertrain part. In addition, it is assumed that $M_{c0\%,\,i}$ is the same as $M_{c,i}$ when the lightweighting degree (d_i) is negative. This is because the relationship between the lightweighting degree and extra cost is not disclosed in Figure 1.

The test weight when the lightweighting degree is 0% can refer to Eqn. (14).

$$M_{t0\%,\,i} = M_{c0\%,\,i} + (M_{t,\,i} - M_{c,\,i}) \tag{14}$$

Where, $M_{t0\%,\,i}$ is the estimated equivalent test weight (kg) of BEV model i when its lightweighting degree is 0%. $M_{t,i}$ is the equivalent test weight (kg) of BEV model i, which is given by Appendix D. $M_{c,i}$ is the curb weight (kg) of BEV model i. $M_{np,i}$ is the non-powertrain part weight (kg) of BEV model i. The results of the estimated equivalent test weight (kg) of BEV models when their lightweighting degrees are 0% are shown by Appendix E. These results are used for evaluating the optimized PCO which varies by vehicle mass in Eqn. (8). The vehicle weights hereinafter all refer to the vehicle equivalent test weight.

4. Results and Discussion

4.1. Impacts of daily range limitation value on BEV's optimal vehicle weight and electric range

The limited electric range of BEVs can cause range anxiety, which is a psychological fear of driving the BEV and being out of power before reaching the destination. One way to measure range anxiety is the daily range limitation value, which represents the backup "rental car" expenditure if the electric range of BEV cannot meet the driver's travel demand in some day (Lin, 2014). The daily range limitation value is positively correlated with the drivers' income (or time value) and could affect the optimal BEV electric range. Based on the driver's income, this study segments the drivers into five groups, as shown in Table 3. The Group 1, who has the highest incomes among the five groups, would have a highest daily range limitation value ($/day). While the Group 2, who are with the least incomes, whose daily range limitation value is least costly. The values of daily range limitation of these five driver groups is estimated by Lin et al in their consumer choice model (Lin et al., 2013).

Table 3. Daily Range Limitation Value for Different Driver Groups by Incomes.

Driver Group #	Daily Range Limitation Value ($/day)
Group 1	228.74
Group 2	187.88
Group 3	151.11
Group 4	118.48
Group 5	89.09

Regarding the lowest PCO as the optimization objective, the optimal vehicle weight of a BEV is found to vary with the daily range limitation value. To validate this statement, this study uses BEV model #6 as an example to quantify the probable optimal vehicle weight under the assumption of lightweighting-cost trend discussed in Section 3 — Methodology. The vehicle performance features of the BEV model #6 can refer to Appendix D. Figure 4 presents the simulation results on the incremental TCO (T): a positive value indicates a relative expenditure, and a negative value indicates a relative saving, compared to the PCO by the current vehicle model design. Therefore, the adjusted vehicle weight should result in a PCO as small as possible in the optimization, which means a best saving. The optimized weight ranges from 1784 kg to 1793 kg as the daily range limitation value decreases from \$228.74 (BEVs for drivers from Group 1) to \$89.09 (BEVs for drivers from Group 2). After the optimization, the saved cost is around \$19 to \$32. The electric ranges in all these five groups of drivers with different daily range limitation values reduced to around 148 mi, and their difference varies small. In addition, relative to the current vehicle equivalent test weight – 1758 kg, the optimal weight can be 30-40 kg heavier so that the comprehensive PCO (T) obtained by Eqn. (8) can be the lowest. This finding suggests that, under the assumed lightweighting-cost trend and from the PCO perspective, the BEV model #6 spends too much on the vehicle lightweighting when designing this vehicle. In addition, compared the optimal vehicle weight among the five groups of drivers with different daily range limitation values, the Group 1 drivers who are with higher incomes and higher range limitation value expect a lighter vehicle weight than the Group 5 drivers who are with lower incomes and lower range limitation value. This is because the Group 1 drivers are more willing/capable to pay more money for time-saving, and their larger value of range anxiety brings about a more urgent need on the longer electric range of BEVs. This requires the BEV to implement more lightweighting technology to save energy consumption, so that the BEVs can be equipped with extended electric range while the battery size keeps the same.

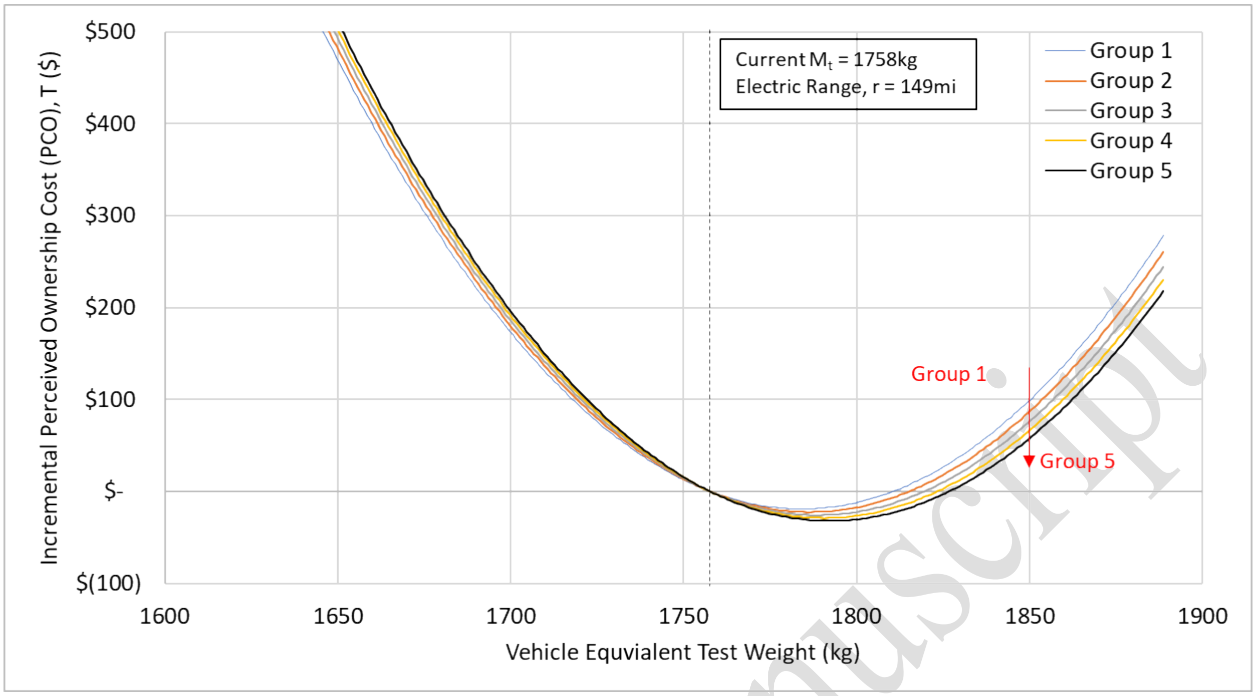


Figure 4. The optimal PCO and electric range for vehicle model #6 varies by the BEV driver's daily range limitation value.

4.2. Impacts of driving patterns on optimal vehicle weight and electric range

As shown in Figure 4, the BEV weights vary as the driver travel patterns are different. Three categories of travel patterns are assumed. (a) The average-traveling driver, whose travel pattern is discussed in Table 2; (b) The frequent-traveling driver, whose daily mean travel distance is 50% more than it is for the average-traveling driver, and all other features are the same; (c) The mild-traveling driver, whose daily mean travel distance is 50% less than it is for the average-traveling driver, and all other features are the same. These three types of drivers are assumed with the same daily range limitation value at $151.11 ("early majority"). Clearly, the optimal electric range for the frequent-traveling driver is more than it is for the average-traveling driver and the mild-traveling driver, respectively. This is because the frequent-traveling driver has the longest annual VMT than others and is eager for more electric range of the BEV.

A lighter vehicle can save more energy and provide longer electric range, thus, the expected ideal vehicle weight for vehicle model #6 is smaller than the current vehicle equivalent test weight (1758 kg) and the ideal vehicle weight for the average/mild-traveling driver. Moreover, because of the lightweighting, the value of the incremental PCO indicates this optimized vehicle weight and electric range can save the frequent-traveling driver around $339 totally. It means that the lightweighting technology contribute more on saving the driver's cost when the BEV model is targeting on the frequent-traveling drivers; and for the average-traveling driver and the mild-traveling driver, the unnecessary emphasis of BEV lightweighting for the vehicle model #6 might not lead to a reduction of drivers' overall PCO.

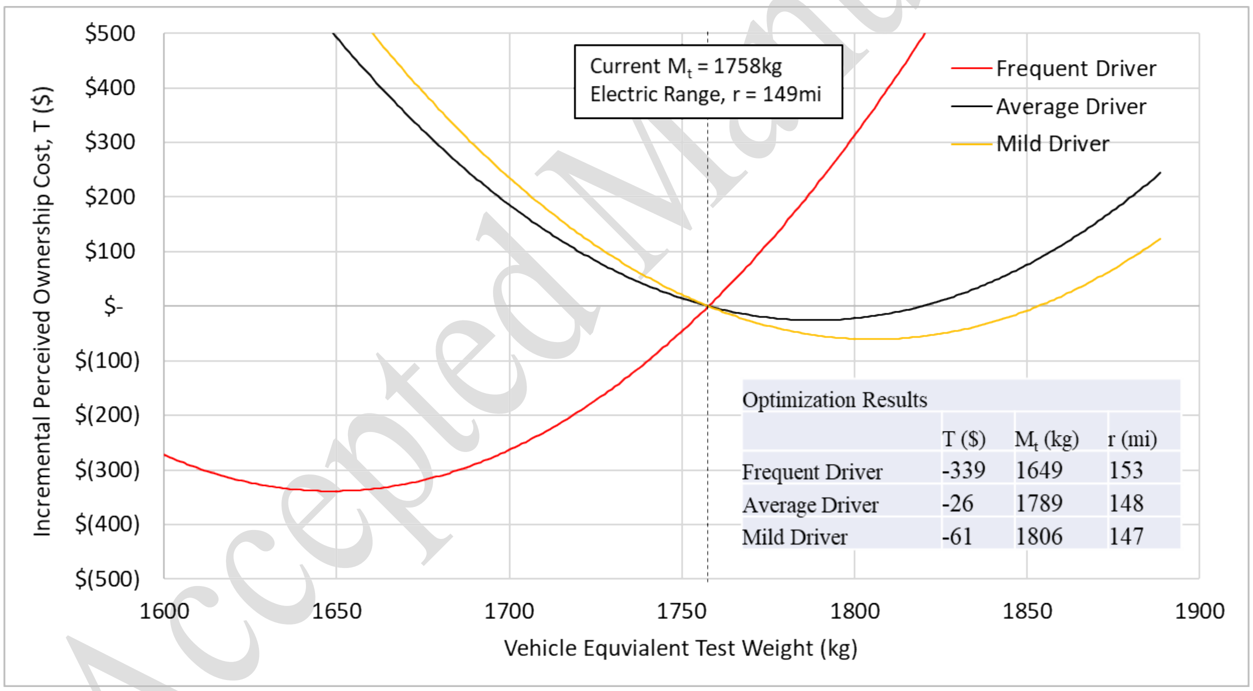


Figure 5. The optimal PCO and electric range for vehicle model #6 varies by the BEV driver's travel pattern.

4.3. Optimized results for different vehicle models

The comprehensive optimization of BEV PCO with consideration of vehicle driving range and vehicle lightweighting is discussed in this section. Because the PCO varies as the BEV driving pattern changes, it is important to define the driver scenario before discussing the optimal vehicle electric range. The daily range limitation value for BEVs is assumed to be $151.11 (“early majority”), as presented in Table 3. This study calculates the vehicle PCO varying with the vehicle weight for the top ten best-selling BEV models in the 2021 U.S. market. Figure 6 shows the simulation results. Because the current vehicle equivalent test weights are different for all the ten vehicle models, the x-axis in Figure 6 shows the vehicle weight ratio which is the vehicle equivalent test weight relative to the Current Vehicle Equivalent Test Weight. The Current Vehicle Equivalent Test Weight is the equivalent test weight for the current vehicle model. The relative PCO is at zero when the ratio is 1. As the vehicle equivalent test weight changes away from the Current Vehicle Equivalent Test Weight, the relative PCO would increase or decrease. The optimal design is reached when the relative PCO is at the minimum of the curve.

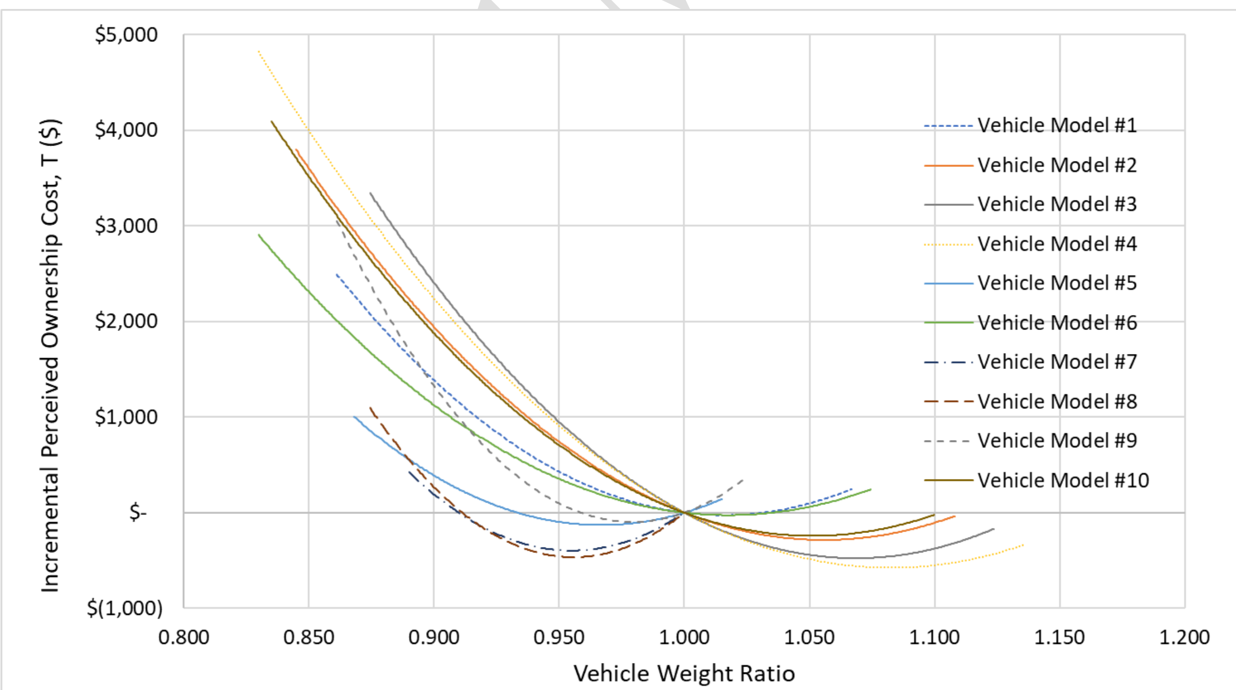


Figure 6. The incremental PCO with respect to the vehicle weight ratio of the ten BEV models, respectively.

It shows that, from the perspective of the PCO, the BEV model is not necessarily to be with more lightweighting or more electric range. As shown in Table 4, for the Vehicle Models #1-4 and 10, the optimized result is that the vehicle weights increase, and the electric ranges reduce relative to the current model features. This is because, as the less lightweighting technology used in the BEV design can help reduce the vehicle price accordingly, the electric range could be compromised as the vehicle becomes heavier, the overall PCO can still save some. At the same time, for the Vehicle Models #5-9, it is suggested that the vehicle models should still need more lightweighting so as to further decrease the PCO relative to the current model design.

Table 4. Simulation Results for Top Ten Best-selling BEVs in the 2021 U.S. Market.

Vehicle#	**Current Equivalent Test Weight (kg)**	**Current Electric Range (mi)**	**Optimized Weight Changes (kg)**	**Optimized Electric Range Changes (mi)**	**Incremental PCO Saved ($)**
Vehicle Model #1	2155	326	+34	-3	26
Vehicle Model #2	1928	353	+107	-10	285
Vehicle Model #3	2381	230	+163	-8	476
Vehicle Model #4	1758	259	+145	-9	575
Vehicle Model #5	2268	260	-75	+4	129
Vehicle Model #6	1758	149	-31	-1	26
Vehicle Model #7	2722	218	-123	+4	396
Vehicle Model #8	2381	200	-106	+4	466
Vehicle Model #9	2155	402	-45	+5	96
Vehicle Model #10	1814	258	+93	-4	243

5. Conclusions

The objective of this study is to construct a method to quantify the weight impacts on BEV's PCO and to determine the optimal electric range accordingly. This method comprehensively associates the physical relationship on vehicle energy consumption rate as well as the economics on vehicle PCO. It can be used to generate optimization-based insights to how lightweighting technology can add lifetime vehicle ownership to accelerate adoption of BEVs. In addition, this study uses the methods to quantify the optimal vehicle weight and electric range for top ten best-selling BEVs in the 2021 U.S. market. It concludes that the optimal design of vehicle electric range and integration of vehicle lightweighting technology should consider the driver incomes (daily range limitation value) and user driving patterns. As the daily range limitation value or the user type changes from $228.74 (BEVs for drivers with highest incomes – Group 1) to $89.09 (BEVs for drivers with least incomes – Group 5), the BEV can ease on lightweighting, as it requires less on the electric range. This is because the range anxiety of the Group 1 drivers is more costly. The frequent-traveling driver could require more on BEV lightweighting than the mild-traveling driver does, because of the higher demand on electric range from the frequent-traveling driver. Considering the optimization of the vehicle weight and electric range for these ten BEV models, we find that it is not always necessary to emphasize the vehicle lightweighting for BEVs; when the lightweighting involves higher vehicle production cost, less lightweighting could reduce the overall PCO to BEV owners.

The major caveat of this study is the relations between vehicle lightweighting degree and extra cost needed, which are generated from the literature review. This relation is very likely to change as auto manufacturer, technology evolution, or materials selection varies. Therefore, the optimal results on vehicle weight and electric range for the BEV model could be different if the relation alters. However, the mathematical derivations of the equations in this method, and the general conclusions achieved by this study are consistent. In sum, the contribution of this study is that it builds a mathematical framework to quantify the BEV optimal weight and electric range; the corresponding model can contribute to the decision-making on the design of BEV performance and features by the auto manufacturers. In the future work, we will consider the lightweighting impacts on the optimization of battery sizing and capacity in electric vehicles, and as more is learnt about the lightweighting cost, the analysis and the model will be updated and improved.

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7. Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: S. Ou, and Z. Lin; data collection: S. Ou, S. Zhang, Z. Lin, and S. Davis; analysis and interpretation of results: S. Ou and Z. Lin; draft manuscript preparation: S. Ou, S. Zhang, and Z. Lin. All authors reviewed the results and approved the final version of the manuscript.

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Appendix A Relation between lightweighting degree (%) and extra cost (%) revealed by Mascarin et al (Mascarin et al., 2015).

	Lightweighting Degree (lbs.)	Lightweighting Degree (%)	Extra Cost ($)	Extra Cost (%)
Baseline Vehicle				
2013 Ford Fusion	0	0.00%	$15,724	0.00%
Substituted Materials				
Optimized Steel 1	106	3.20%	$15,522	-1.28%
Optimized Steel 2	462	14.00%	$15,389	-2.13%
Optimized Steel 3	546	16.50%	$15,291	-2.75%
Aluminum Intensive 1	367	11.10%	$16,070	2.20%
Aluminum Intensive 4	1175	35.60%	$16,706	6.25%
MultiMaterial 1	167	5.00%	$16,107	2.44%
MultiMaterial 2	701	21.20%	$16,484	4.83%
MultiMaterial 3	812	24.60%	$16,833	7.05%
MultiMaterial 4	1220	36.90%	$20,036	27.42%
Carbon 1	462	14.00%	$21,705	38.04%
Carbon 4	1271	38.50%	$22,307	41.87%
Carbon 5	1493	45.20%	$25,211	60.33%

Appendix B Relation between lightweighting degree (%) and extra cost (%) revealed by Islam et al (Islam et al., 2020).

Vehicle Type*		Baseline	MY# 2025	MY 2030	MY 2035	MY 2050
Compact car (Low)	Lightweighting Degree	0%	4%	5%	5%	5%
	Extra cost	0%	8%	11%	11%	10%
Compact car (High)	Lightweighting Degree	0%	11%	18%	19%	19%
	Extra cost	0%	15%	24%	26%	21%
Midsize car (Low)	Lightweighting Degree	0%	8%	10%	10%	10%
	Extra cost	0%	15%	19%	19%	17%
Midsize car (High)	Lightweighting Degree	0%	16%	25%	30%	32%
	Extra cost	0%	20%	31%	37%	32%
Small SUV (Low)	Lightweighting Degree	0%	7%	10%	14%	18%
	Extra cost	0%	11%	15%	22%	25%
Small SUV (High)	Lightweighting Degree	0%	12%	18%	22%	28%
	Extra cost	0%	13%	19%	23%	24%
Midsize SUV (Low)	Lightweighting Degree	0%	11%	13%	17%	21%
	Extra cost	0%	17%	19%	26%	28%
Midsize SUV (High)	Lightweighting Degree	0%	13%	20%	24%	30%
	Extra cost	0%	13%	20%	24%	25%
Pickup (Low)	Lightweighting Degree	0%	12%	14%	17%	22%
	Extra cost	0%	19%	23%	28%	31%
Pickup (High)	Lightweighting Degree	0%	12%	21%	24%	28%
	Extra cost	0%	12%	22%	25%	24%

* There are two types of technology projection scenarios: Low—lightweighting technology evolution develops low; High—lightweighting technology evolution develops high.

MY—model year.

Appendix C Relation between lightweighting degree (%) and extra cost (%) revealed by Bailo et al (Bailo et al., 2020).

	Lightweighting Degree	Extra Cost
Baseline	0%	0%
Scenario 1* (Low#)	0.69%	5.42%
Scenario 2 (Low)	22.84%	118.05%
Scenario 3 (Low)	4.86%	13.08%
Scenario 1 (High)	0.69%	4.81%
Scenario 2 (High)	22.84%	109.89%
Scenario 3 (High)	4.86%	12.38%

There are two types of projection scenarios: Low—electrification technology evolution develops low; High—electrification technology evolution develops high.

* Three types of lightweighting materials penetration scenarios: 1, 2, and 3. The penetration scenario is presented below:

Scenario	Expected Material Trend
Baseline 2020	Body: HSS, AHSS, UHSS Closures: HSS, low Al
Scenario 1	Body: HSS, AHSS, UHSS Closures: HSS, Al
Scenario 2	Body: Aluminum, AHSS, UHSS Closures: Al, comp, Mag
Scenario 3	Body: AHSS, UHSS, low Al Closures: Al

Appendix D Vehicle Performance Features (all units have been translated to metric units) of Vehicle Models Used for Lightweighting-Electric Range Relationship Quantification

No.	Vehicle Maker	Vehicle Model
1	Tesla	Model Y Long Range AWD
2	Tesla	Model 3 Long Range AWD
3	Ford	Mach-E
4	CHEVROLET	BOLT EV
5	Volkswagen	ID.4 AWD Pro
6	NISSAN	LEAF
7	AUDI	Audi e-tron Quattro Sportback
8	Porsche	Taycan 4S Perf Battery
9	Tesla	Model S Long Range
10	HYUNDAI	Kona Electric

No.	Sales in 2021	Battery Size (kWh)	Electric Range (miles)	Coast-down Coefficient (A, N)	Coast-down Coefficient (B, N/(m/s))	Coast-down Coefficient (C, $N/(m/s)^2$)	Equivalent Test Weight (kg)	Curb Weight (kg)	Energy Consumption rate (L_{eq}/100km)	Footprint (m^2)	Height (m)
1	172,700	75	326	152.44	3.18	0.32	2155	2012	1.88	4.79	1.62
2	128,600	82	353	155.60	0.86	0.33	1928	1828	1.76	4.54	1.44
3	27,140	91	230	208.04	2.59	0.46	2381	1993	2.42	4.83	1.60
4	24,803	66	259	126.29	2.01	0.43	1758	1616	1.99	3.90	1.60
5	16,742	82	260	126.11	4.43	0.36	2268	2141	2.42	4.39	1.64
6	14,239	40	149	115.16	3.43	0.43	1758	1588	2.12	4.20	1.56
7	10,921	95	218	159.00	3.85	0.40	2722	2608	3.05	4.85	1.66
8	9,419	79	200	186.70	4.32	0.27	2381	2247	2.98	4.97	1.38
9	9,100	100	402	128.95	4.57	0.25	2155	2215	1.96	5.03	1.45
10	8,936	64	258	110.58	-1.99	0.53	1814	1685	1.96	4.10	1.55

Appendix E Vehicle Weight Information (all units have been translated to metric units)

No.	Equivalent Test Weight (kg)	Curb Weight (kg)	Battery System Weight (kg)	Motor System Weight (kg)	Powertrain Other Part Weight (kg)	Powertrain Weight (kg)	Non - powertrain Weight (kg)	Lightweighting Degree	Equivalent Test Weight if Lightweighting Degree is 0% (kg)
1	2155	2012	450	115	306	871	1142	11.15%	2298
2	1928	1828	492	154	306	952	876	19.17%	2135
3	2381	1993	546	156	306	1008	985	22.96%	2675
4	1758	1616	396	123	306	825	792	23.14%	1996
5	2268	2141	492	185	306	983	1158	2.82%	2302
6	1758	1588	240	90	306	636	952	12.05%	1888
7	2722	2608	570	103	306	979	1629	-22.10%	2722
8	2381	2247	475	148	306	929	1318	-16.18%	2381
9	2155	2215	600	159	306	1065	1150	4.29%	2206
10	1814	1685	384	123	306	813	872	17.19%	1995