Range Prediction based on Battery Degradation and Vehicle Mileage for Battery Electric Vehicles

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Abstract: ***Due to their low - carbon and ecologically benign characteristics, electric vehicles are growing in popularity. With the aim of creating electric vehicles that can match or even outperform today's internal combustion engines, extensive studies have been done considering the depletion of fossil resources, and changes in climate brought on by air pollution. Over the course of a vehicle's lifespan, switching to electric vehicles (EVs) can dramatically cut greenhouse gas emissions from internal combustion engine (ICE) vehicles. Because batteries have a high - power density and a consistent output voltage across all EV types, they are a popular energy storage option. Long recharge times, the limitations of current electrical infrastructure, low public acceptance, and high startup expenses are the drawbacks of battery - powered electric vehicles. As a battery's capacity deteriorates throughout the life of the battery, the travel distance is shortened. A thorough analysis of the techniques utilized to address battery degradation in electric vehicles is addressed. This review describes the relationship of battery degradation as a vehicle's mileage increases, and what factors go into battery degradation.***

Keywords: Electric vehicles, Battery performance, battery degradation, mileage, lithium - ion, energy storage

1. Introduction

Innovations in battery and motor technology facilitated the development of electric cars. For the microgrid, an electric vehicle (EV) can serve as a load and a distributed energy resource. An EV has an electric motor that is powered by batteries that store energy. Compared to traditional internal combustion engine (ICE) vehicles, EVs are a sharp contrast. Additionally, they produce no emissions and are substantially more environmentally friendly than vehicles powered by liquified petroleum gas. Compared to gasoline - powered vehicles, EVs consume less fuel and make less noise. Because ICE vehicles have more moving components than electric vehicles, they require more frequent maintenance. When there is no engine or exhaust, no tune - ups, timing adjustments, or oil changes are needed. EVs have sparked a great deal of attention over the past ten years as one of the best strategies to lower greenhouse gas emissions. Additionally, they provide a calmer and more hygienic environment. The early adoption of EVs has been fueled by the increasing worldwide demand for fossil fuels and their inexorable depletion. Additionally, EVs have a distinct advantage in terms of integration flexibility, which translates into improved transportation performance. EVs can use a range of energy sources, including fuel cells, solar panels, regenerative braking, capacitors and ultracapacitors, and supercapacitors. EV adoption has been going slow, with retail sales dominating the EV business, despite technological advances and EV incentives including low operating costs and access to renewable energy. The biggest barriers to their acceptance are high upfront prices, high investment costs, and limited driving ranges brought on by the battery. Range of battery charge is one of the largest drawbacks to electric vehicles, with the range significantly decreasing as the life of the battery and vehicle increases. Additionally, there are many obstacles that must be overcome before EVs can be widely adopted, including charger compatibility, infrastructure availability and improvement, grid capacity, and automobile costs.

1.1. Objective

The objective of this paper is to understand the relationship between an electric vehicle’s mileage and the battery capacity. A linear regression was conducted to develop this model.

2. Literature Review

How to reduce battery degradation and extend the battery's useful life is the main issue with electric car batteries. This is investigated in light of various charging techniques and the potential benefits of leveraging vehicle - to - grid services to extend battery life. The external temperature and circumstances, heat produced during charging and discharging and its capacity to disperse, as well as the various driving patterns, make it difficult to evaluate the degradation (Wang, et al, 2016).

Lithium ion batteries are more used for use in electric vehicles, and engineers can make batteries that last longer by studying the degradation of these battery cells. When compared to the nominal electrolyte salt concentration, the conducting salt $LiPF_6$ showed a significant breakdown in 19 samples. High - power batteries had high - weight portions of dimethyl carbonate to accommodate for the higher charging rates during usage, whereas high - energy batteries had larger weight portions of ethyl methyl carbonate and diethyl carbonate (Henschel et al., 2020).

The most typical battery in EVs is a lithium - ion battery. Performance characteristics for charge time and range per charge, dependability, and safety are factors that affect the use of Li - ion batteries. The latter requires special care due to the battery's volatile nature and high energy, which can result in fires or explosions. Recalls are growing along with the EV market boom. Safety - related recalls that mention fire are not just linked to collisions but also to incidents that don't involve collisions. Batteries have been known to catch fire and even explode in some cases. These stories, all of which occurred in 2020, indicate the rise in quality control problems that put the EV industry at risk of fires (Ryan

Aalund, 2021).

2.1. Emission Impacts

Electric vehicles don't cause a lot of pollution, but the power plants that make the electricity for the charging stations do. To determine the system average emission factors, we first compute the emission consequences of various types of power stations' fuel mixes. We develop scenarios for electric vehicle usage and pollution control solutions for power plants. Results of EV emission implications are shown as per - mile emission reductions. While epa controls evaporative HC, carb controls the emission rates of HC, CO, and nox. Since diurnal emissions depend on the number of vehicles, rather than the number of kilometres travelled, they are calculated as a percentage of each model - year EV to all model - year EVs in a target year. (Quanlu Wang, 2012).

2.2. Material Sustainability

Electric machines are a key part of the BEV propulsion system, and high - performance and low - cost electric machines are desirable in the mass production of BEVs. There are several available approaches for manufacturing management, such as Lean manufacturing, total quality management and six sigma. Lean manufacturing is a systematic method for waste minimization without sacrificing productivity in a manufacturing system, with advances in electric machine design technologies, the permanent magnet synchronous machine has become one of the most promising solutions for BEV applications due to its remarkable features of high torque density, excellent controllability, and good efficiency. Most of the permanent magnets in high - performance are made of high - energy rare - earth materials that provide high residual flux density, but their soaring price and uncertainty in the supply chain have been a major concern. Ferrite magnet as an alternative pm is drawing considerable interest from both academics and industry due to its abundant raw material resources, low price, stability to corrosion and temperature, easy manufacture, and very high electrical resistivity. In order to improve the overall quality of mass - production electric machines for BEV applications, the doe - assisted six sigma method is proposed for quality control, the machine quality is improved by minimizing the variation of output torque and efficiency (D. M. Wu. C. K. P. Luk, 2017). The demand for oil, coal, and gas is increasing globally, mainly due to an increase in per capita - energy consumption and demand for electricity in all the sectors. Because of limited oil and coal reserves on the planet and stringent emission norms, researchers are forced to think of alternative methods for sustainable power generation and energy supply. So, in the transportation sector, electric vehicles (EVs) can play a major role toward mitigating the environmental problems with sustainability (Akhil Garg, 2019). EV vehicles are also considered as ecofriendly vehicles. In battery powered EV, the battery packs are the heart of the vehicle because it provides the primary energy to run the vehicle efficiently. So, in this the author show us a various method for how we can check the battery health, charging and possible solutions for that. while considering the impact of charging speeds on battery life more generally.

2.3. Battery Health

We also have identified a lack of clear guidance for prospective EV purchasers and for charging infrastructure providers on the interactions between battery types, range, charging times, rate of charge, and battery life. Here, We define battery life and the processes causing battery degradation, then review the sparse literature empirically testing battery degradation. As degradation and the impact of charging speeds are dependent on the size and type of battery. The impact of charging speeds are dependent on the size and type of battery (Engel et al.2019). Apart from that, the major reason for EVs not becoming more widely popular is their limited range. They found that while increasing the capacity of EV batteries would reduce range anxiety and make EVs more attractive for purchase, the current costs are still prohibitive (Hitomi Sato, 2017). So, basically the author's purpose is to collect all the data from different year model cars users and then analyze it to see how they can improve the range of vehicles. As the electric motor play an important role for BEV vehicles so through the analysis and comparison of direct current motor, induction motor, and synchronous motor, it is found that permanent magnet synchronous motor has better overall performance; by comparison with converters with Sibased IGBTs, it is found converters with SiC MOSFETs show significantly higher efficiency and increase driving mileage per charge. In addition, the pros and cons of different control strategies and algorithms are demonstrated. Furthermore, Another factor which is considered for the significant impact on the battery range is climate conditions as the range is decreasing with extremely low and high temperature. Manufactures of electric vehicles sometimes use an electric preheat function to warm up the battery during charging. Technical condition of the vehicle is also important, especially accurate tire pressure. The range also affects the use of comfort features such as an air conditioner or heating. To reduce the driving range anxiety and hence to support a stronger increase of the penetration of EVs worldwide there is the need of a charging system which is able to replace the current existing oil station. A fast-charging station (FCS) can allow the charging of an EV at 80% within a half hour from its depletion, but to reduce the charging time from 7–8 h to 30 min (Carola leone, 2020).

2.4. Battery charging and discharging

Here, for the charging technology the main purpose of this technology is to show the various types of converter we can use to charge batteries as fast as possible. The main purpose is to implant the faster charging stations so that customers just charge their batteries for just a few minutes and they can get a maximum range. Measuring electric vehicle battery health is a complicated process that requires several different inputs that ensure every aspect of the battery health is measured. Using block chain, a distributed ledger that links blocks using cryptography, it will track the charging/discharging power and operating temperature to generate the vehicle’s battery degradation cost (Gowda et al., 2021). It is extremely important to find a balance between the optimization of electric vehicle battery health while also staying relatively affordable to the general consumer. Being able to understand the degradation of the battery using real life inputs but also being fast enough to understand and improve is also important for engineers to be able to improve battery performance as quickly as the electric vehicle market is growing (Jin, 2017).

3. Methods

In order to collect the data for this paper and analysis, research was done to find electric vehicle mileage and the respective battery capacity. Merijn Coumans started a survey via the Dutch - Belgium Tesla forum in 2014 to collect Tesla owners data and understand a real life battery degradation. The survey asks several questions to understand how the battery is degrading. It starts with what region the owner resides in, the manufacturing date of the vehicle, and which model it is. Then it asks questions relating to how the vehicle is charged and discharged, such as how frequently the owner supercharges the vehicle, how often it is charged entirely to 100%, how often the range gets lower than 5%, and the daily level that the vehicle is charged. Next the survey covers some questions relating to range, what the range was at 100% when the car was new, and the range it is rated for. The final questions are entered for as many entries as possible, typically every 5, 000 miles. This asks for when the vehicle was last charged to 100% and the mileage at that time, then it calculates the remaining battery capacity based on the entries. how often it is charged entirely to 100%, how often the range gets lower than 5%, and the daily level that the vehicle is charged. Next the survey covers some questions relating to range, what the range was at 100% when the car was new, and the range it is rated for. The final questions are entered for as many entries as possible, typically every 5, 000 miles. This asks for when the vehicle was last charged to 100% and the mileage at that time, then it calculates the remaining battery capacity based on the entries. Owners were encouraged to input multiple entries, and many have been adding their data since 2014 to present day.

4. Data Collection

Table 1 shows the first 200 data points collected of mileage and calculated battery capacity of Tesla Model S.

Table 1: Data of Mileage and Battery Capacity for Tesla Model S owners around the world (Coumans, 2014)

Remaining battery capacity	*Mileage [mi]*	*Remaining battery capacity*	*Mileage [mi]*	*Remaining battery capacity*	*Mileage [mi]*	*Remaining battery capacity*	*Mileage [mi]*
87.20%	100, 244	89.39%	102, 409	123.33%	4, 320	97.62%	3, 107
91.20%	80, 207	91.43%	97, 095	120.20%	13, 822	97.62%	3, 106
90.63%	74, 600	91.02%	92, 236	94.27%	69, 904	71.43%	249
90.63%	140, 552	90.01%	87, 571	95.76%	59, 758	87.59%	111, 942
121.07%	37, 083	91.84%	82, 170	92.28%	61, 954	91.10%	70, 220
88.86%	134, 061	92.24%	77, 096	91.89%	82, 447	89.10%	73, 850
86.87%	103, 000	93.06%	72, 094	94.18%	72, 079	83.46%	213, 450
105.63%	16, 455	93.47%	67, 195	93.96%	51, 237	94.63%	263
104.93%	21, 989	93.88%	62, 095	100.52%	2, 341	78.20%	130, 000
102.11%	41, 344	94.69%	57, 153	98.44%	7, 133	93.67%	119, 094
104.93%	27, 301	89.87%	136, 164	97.40%	11, 462	117.45%	49, 088
99.30%	55, 030	82.71%	116, 000	96.35%	16, 631	92.31%	91, 373
96.43%	205	94.51%	48, 467	96.35%	28, 440	92.80%	76, 607
81.91%	132, 872	90.89%	75, 774	96.35%	28, 440	92.80%	78, 841
93.03%	129, 190	89.95%	148, 761	95.31%	32, 118	92.56%	81, 286
93.23%	111, 970	87.85%	175, 244	98.34%	31, 069	92.56%	88, 611
85.34%	154, 137	92.48%	112, 172	89.58%	49, 930	92.97%	45, 904
89.47%	178, 590	91.35%	122, 030	105.57%	156, 896	92.66%	173, 984
87.97%	202, 409	90.60%	127, 195	83.54%	178, 597	92.66%	175, 227
92.71%	197, 878	90.23%	133, 778	92.28%	47, 500	93.23%	54, 537
92.47%	209, 136	95.00%	68, 351	115.48%	4, 110	89.62%	233, 014
92.39%	74, 875	94.18%	93, 203	78.20%	123, 473	96.35%	15, 534
94.85%	34, 773	93.16%	111, 115	88.35%	124, 057	80.68%	76, 721
93.29%	78, 914	86.87%	71, 800	92.47%	70, 206	91.35%	82, 015
92.39%	88, 794	89.58%	61, 000	87.59%	145, 597	109.90%	497
91.72%	98, 798	94.43%	82, 396	92.66%	94, 448	109.70%	3, 664
90.60%	105, 913	92.91%	92, 646	93.06%	136, 080	93.67%	123, 901
89.77%	109, 775	97.65%	77, 746	94.79%	47, 024	87.34%	214
89.77%	111, 864	113.06%	79, 900	92.56%	52, 805	95.75%	38, 525
89.21%	116, 836	95.00%	102, 091	93.30%	64, 431	90.35%	55, 934
88.81%	119, 117	94.72%	109, 567	93.30%	70, 146	88.35%	236, 559
89.49%	125, 144	91.67%	139, 498	87.92%	154, 207	88.72%	214
94.43%	37, 904	91.94%	160, 155	95.95%	26, 454	90.60%	194, 298
90.38%	137, 882	96.67%	61, 205	96.46%	51, 903	89.85%	175, 605
95.86%	47, 500	93.06%	70, 992	91.65%	121, 167	88.72%	218, 057
90.89%	110, 604	89.60%	74, 040	96.46%	51, 903	94.62%	31, 306
93.42%	117, 639	91.73%	60, 646	92.62%	71, 147	98.66%	40, 087
91.65%	125, 264	95.47%	31, 069	94.35%	128, 624	94.35%	140, 430
92.91%	127, 845	86.96%	65, 000	93.67%	55, 118	93.98%	57, 159

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89.37%	154, 721	120.39%	38, 940	113.11%	70, 339	96.47%	36, 040
89.11%	195, 732	94.67%	221	88.00%	46, 056	85.28%	129, 742
92.55%	41, 010	98.70%	56, 017	88.24%	47, 331	94.41%	49, 710
91.96%	45, 981	97.92%	62, 269	112.78%	6, 054	94.17%	37, 158
169.01%	124	97.40%	64, 424	95.93%	46, 700	95.79%	86, 992
158.45%	6, 214	100.52%	31, 069	90.65%	53, 185	91.14%	85, 128
154.93%	12, 427	100.26%	24, 855	89.43%	55, 700	97.52%	14, 206
94.43%	82, 102	98.96%	52, 817	96.24%	97, 252	96.48%	19, 914
90.13%	112, 328	98.44%	57, 166	95.53%	59, 652	96.48%	23, 040
89.11%	126, 983	93.98%	109, 200	94.29%	65, 244	94.20%	31, 680
101.11%	823	123.73%	117	98.06%	24, 855	98.82%	9

5. Analysis

A scatterplot of the battery capacity and mileage was created to visually represent the data represented in Table 1. The graph is shown in Figure 1. The scatterplot shows that as mileage increases, the capacity of the battery decreases. As it is shown in the scatterplot, there are some outliers. This can be due to bad information uploaded into the survey and is effectively ignored in the analysis.

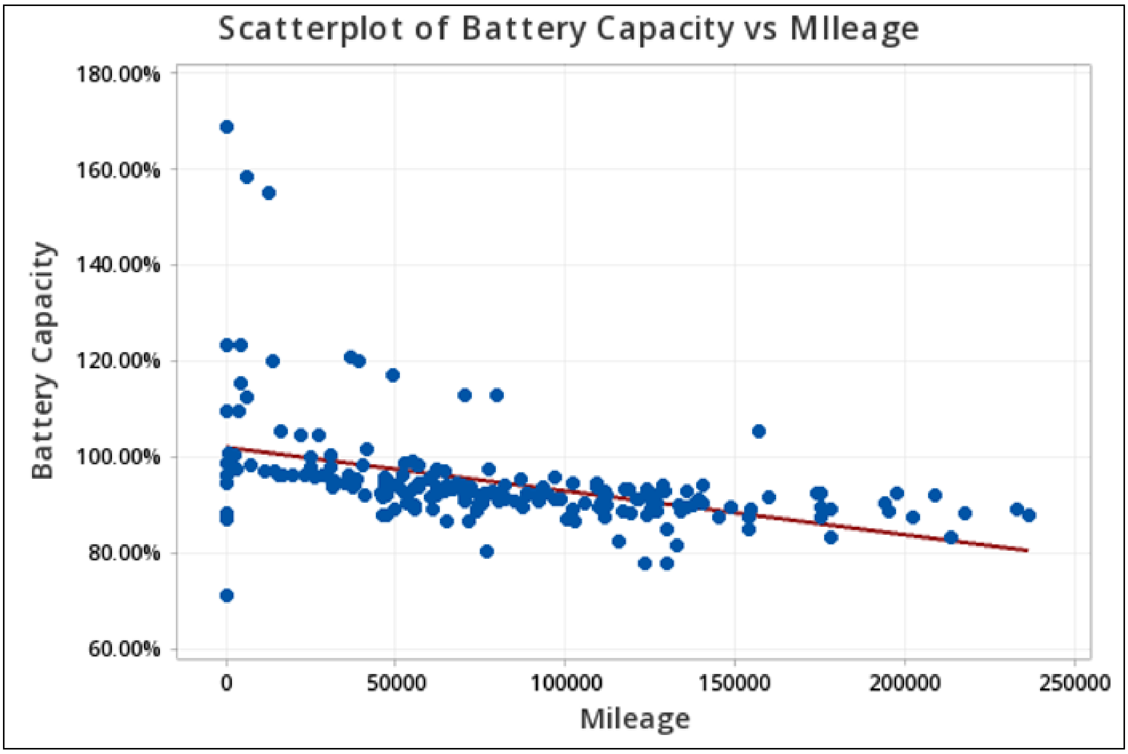

Figure 1: Scatterplot of Data

After looking at the scatterplot, the best fit regression equation, described in Figure 2, was found to better explain the data. There is a definite negative correlation between the mileage and the battery capacity. As the mileage increases, the battery capacity decreases.

Regression Equation

Battery Capacity = 1.0232 - 0.000001 Mileage

Figure 2: Equation of Regression Model

Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	1.0232	0.0125	81.74	0.000	
Mileage	-0.000001	0.000000	-6.92	0.000	1.00

Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0988226	19.47%	19.06%	17.25%

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	1	0.46737	0.467374	47.86	0.000
Mileage	1	0.46737	0.467374	47.86	0.000
Error	198	1.93365	0.009766		
Lack-of-Fit	191	1.93139	0.010112	31.31	0.000
Pure Error	7	0.00226	0.000323		
Total	199	2.40102			

Figure 3: Further Regression Analysis from Minitab

The Model Summary in Figure 3 gives further information about how the regression equation fits the data. The S value

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determines how well the data values fall from the fitted values. A low S value shows that the model describes the response well. On the other hand, the R^2 value of 19% says there is not a strong correlation of the response in the model, and the predicted R^2 value gives an even less correlation of future values being well correlated to the model. This can be seen by the fitted line in Figure 1, which represents the regression equation in Figure 2.

5.2 Degradation Models

According to the Tesla warranty for Model S vehicles, the Battery and Drive Unit limited warranty covers all replacement for a period of 8 years or 150, 000 miles with a minimum of 70% battery capacity. Based on this, the regression equation was set to 70% and solved for mileage to benchmark the estimated mileage that a battery for an electric vehicle will need replacement or suffer significant reduction in ability. From this assumption, and the regression equation in Figure 2, the mileage at which the battery in a Tesla Model S will reach 70% of its capacity is 323, 200 miles. Following the average yearly miles driven of 12, 000 miles, it would take the consumer about twenty - seven years to reach. The average lifespan of an internal combustion engine is around 200, 000 miles and this estimation far exceeds that.

5.3 Impact of Battery degradation on Fuel Economy Numbers

Below is the BEV fuel economy curves data generated using the Vehicle Attribute Model from the National Petroleum Council's "Advancing Technology for America's Transportation Future" study, which can be accessed on the NPC website. The input values used for this analysis are presented in Table 2. The NPC Vehicle Attribute Model was specifically designed to provide outcomes for a BEV100 (a BEV with a range of 100 miles) across various input parameter values. However, for this study, the Vehicle Attribute Model was adjusted to maintain the inputs specified in Table 2 while altering the vehicle's driving range, resulting in a range of results for BEV10 to BEV300 (ranging from 10 to 300 miles on - road range). Figure 4 illustrates the relationship between BEV price, fuel economy, and range. Additionally, Figure 4 includes data points from currently available BEVs in the US market, which demonstrate a reasonable alignment with the modeled curves [2].

Table 2: Vehicle Attribute Model Inputs

Input Parameters	Setting	Details
Vehicle Class	Medium SUV	Corresponds to Two - Seater, Mini - compact, subcompact, and Compact classes in EINS Annual Energy Outlook data set
Year	2019	Vehicle production year
Vehicle Tech Price	Lower Bound	$210 incremental price for 10% BEV fuel economy improvement; $570 for 15%; $1, 470 for 20%
Battery Price	Lower Bound	$405 OEM cost per nominal kWh; $525 per usable kWh; $740 final price to consumer per usable kWh vehicle - mass effects.
Oil Price	Reference	$0.191 per kWh electricity price, including EVSE installation $3.43 per gallon gasoline
Charging Scenario	Home Only	Home Charging Only
Time Horizon	3 years	Used in setting vehicle design point. Model selects point on trade - off curve that minimizes vehicle purchase price + 3 years' fuel expenditure

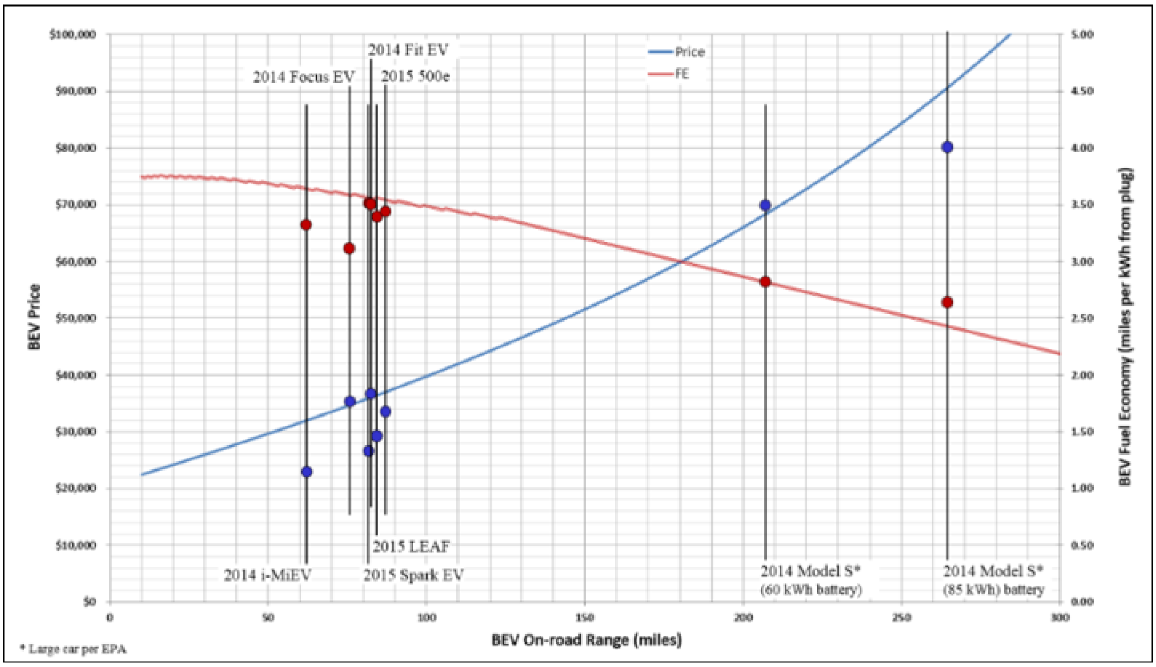

Figure 4: BEV Price Fuel Economy VS Range

Figure 2 illustrates an upward sloping price curve and a downward sloping fuel economy curve, both of which are influenced by battery mass effects. An increase in battery size leads to a reduction in fuel economy, resulting in the need for more incremental battery energy to achieve additional miles of range. The Vehicle Attribute Model for BEVs assumed that a 10% increase in overall vehicle mass would lead to a 4% increase in fuel consumption. Additionally, the model assumed a 50% mass compounding factor, indicating that for every pound of battery added, an extra half pound of secondary mass is required for supporting functions such as the support structure, suspension, and brakes.

6. Results

From the regression analysis, there is clear degradation of an electric vehicle battery as the vehicle mileage increases. The main concern with electric vehicles is the lasting performance of the battery and if it is comparable to a standard internal combustion engine that exists today. Tesla is the longest running electric vehicle company currently, and from Coumans survey, many of the vehicles are lasting well over 250, 000 miles. This outlasts many ICE vehicles on the market, and gives hope to the electric vehicle industry. It is also clear that the level of degradation in a standard vehicle's lifespan is not as significant, and a majority of batteries maintain high capacity for the first 150, 000 miles of their use.

7. Conclusion

This paper has shown that the development of batteries for electric vehicles still has a long way to go before being optimal for the standard consumer. It has proven through the analysis that the significant degradation of electric batteries begins after 200, 000 miles. When the battery capacity of an electric vehicle reaches 70%, there is significant degradation in the performance of the battery, and from the analysis this capacity would not be reached until the vehicle reaches 323, 000 miles. It is important to understand that the level of degradation of these batteries is not high, and many electric vehicles will either match or exceed the lifespan of a standard internal combustion engine.

References

[1] Cai, W., Wu, X., Zhou, M. et al. Review and Development of Electric Motor Systems and Electric Powertrains for New Energy Vehicles. Automot. Innov.4, 3–22 (2021). https: //doi. org/10.1007/s42154 - 021 - 00139 - z

[2] Coumans, Merjin. Tesla Battery Survey.2014 https: //docs. google. com/spreadsheets/d/1c3m9wqlxPBo8ziDYVm5cHRz NCHZbtI_2vVhlXksX9Jc/edit# gid=1304697563

[3] D. M. Wu, C. K. P. Luk and W. Z. Fei, "Quality control of low - cost electric machines for electric vehicles by DOE assisted six sigma DMADV method, " 2017 7th International Conference on Power Electronics Systems and Applications - Smart Mobility, Power Transfer & Security (PESA), Hong Kong, 2017, pp.1 - 8, doi: 10.1109/PESA.2017.8277740

[4] Geotab introduces ev battery degradation tool, providing assessment and comparison of electric vehicle battery life. (2020). Investment Weekly News, 213, 213–213.

[5] Gowda, S. N., Eraqi, B. A., Nazaripouya, H., & Gadh, R. (2021). Assessment and Tracking Electric Vehicle Battery Degradation Cost using Blockchain.2021 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT). doi: 10.1109/isgt49243.2021.9372218

[6] Impact of the use of electric vehicles in collaborative urban transport networks: A case study Andrés Muñoz - Villamizar, Jairo R. Montoya - Torres, Javier Faulin

[7] Jin, X., &PurdueUniversity. Mechanical Engineering. (2017). Physics - based computationally efficient battery degradation model and electric machine scaling strategy for hybrid electric vehicle design optimization (dissertation). ProQuest Dissertations & Theses.

[8] Sajad Bijanvand; Mirali Mohammadi; Abbas Parsaie; Vishwanadham Mandala, Modeling of discharge in compound open channels with convergent and divergent floodplains using soft computing methods, Journal of Hydroinformatics (2023) 25 (5): 1713–1727, https: //doi. org/10.2166/hydro.2023.014Martin Mruzeka, Igor Gajdaca, Ľuboss Kucera, Tomas Gajdosika. The Possibilities of Increasing the Electric Vehicle Range. https: //doi. org/10.1016/j. proeng.2017.06.107

[9] Mokesioluwa Fanoro, Mladen Božani and Saurabh Sinha. A Review of the Impact of Battery Degradation on Energy Management Systems with a Special Emphasis on Electric Vehicles

[10] Mothilal Bhagavathy, Sivapriya, Hannah Budnitz, Tim Schwanen, and Malcolm McCulloch.2021. "Impact of Charging Rates on Electric Vehicle Battery Life. " Findings, March. https: //doi. org/10.32866/001c.21459.

[11] Morris Brenna, Federica Foiadelli, Carola leone & Michela Longo. Journal of Electrical Engineering & Technology. Electric Vehicles Charging Technology Review and Optimal Size Estimation. https: //link. springer. com/article/10.1007/s42835 - 020 - 00547 - x

[12] Quanlu Wang, Mark A. DeLuchi & Daniel Sperling (1990) Emission Impacts of Electric Vehicles, Journal of the Air & Waste Management Association, 40: 9, 1275 - 1284, DOI: 10.1080/10473289.1990.10466782

[13] V. Mandala, M. A. R. Jeyarani, A. Kousalya, P. M and M. Arumugam, "An Innovative Development with Multidisciplinary Perspective in Metaverse Integrating with Blockchain Technology with Cloud Computing Techniques, " 2023 International Conference on Inventive Computation Technologies (ICICT), Lalitpur, Nepal, 2023, pp.1182 - 1187, doi: 10.1109/ICICT57646.2023.10134108.

[14] Sudipta Bijoy Sarmah, Pankaj Kalita, Akhil Garg, Xiao - dong Niu, Xing - Wei Zhang, Xiongbin Peng, Dipanwita Bhattacharjee. J. Electrochem. En. Conv. Stor. Nov 2019, 16 (4): 040801. A Review of State of Health Estimation of Energy Storage Systems: Challenges and Possible Solutions for Futuristic Applications of Li - Ion Battery Packs in Electric Vehicles. https: //doi. org/10.1115/1.4042987

[15] Tomio Miwa, Hitomi Sato, Takayuki Morikawa, "Range and Battery Depletion Concerns with Electric Vehicles", Journal of Advanced Transportation, vol.2017, Article ID 7491234, 12 pages, 2017. https:

//doi. org/10.1155/2017/7491234
[16] Understanding the Non - Collision Related Battery Safety Risks in Electric Vehicles a Case Study in Electric Vehicle Recalls and the LG Chem Battery RYAN AALUND, (Member, IEEE), WEIPING DIAO, LINGXI KONG, AND MICHAEL PECHT
[17] Suresh, P., Poongodi, T., Balamurugan, B., & Sharma, M. (Eds.). (2022) et al. Big Data Analytics in Smart Manufacturing: Principles and Practices (1st ed.). Chapman and Hall/CRC. https: //doi. org/10.1201/9781003202776.
[18] V. Mandala, R. Rajavarman, C. Jamunadevi, R. Janani and Dr. T. Avudaiappan, "Recognition of E - Commerce through Big Data Classification and Data Mining Techniques Involving Artificial Intelligence, " 2023 8th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2023, pp.720 - 727, doi: 10.1109/ICCES57224.2023.10192673.

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