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Influential Factors on the Type Approval Electric Driving Range of Electric Vehicles

Seiho Kim[1], Jaesik Lee[2], Jaejin Kim[3]

[1]*IHS Markit Korea, 322 Yanghyeon-ro, Bundang-gu, Seongnam-si, Gyeonggi-do, 13496, South Korea, richard.kim@ihsmarkit.com*

[2]*Graduate School of Management of Intellectual Property, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul 02841, South Korea, tieangel@korea.ac.kr*

[3]*College of Engineering, Yeonsei University, 50 Yeonsei-ro, Seodaemoon-gu, Seoul 03722, South Korea, jjkim2212@yonsei.ac.kr*

Summary

High anxiety among consumers with regard to the driving range of battery electric vehicles (BEV) is a psychological and practical barrier for a wide-scale market uptake of such vehicles. In this regard, many academic and empirical researches focus on BEV's real-world driving range measurement and estimation to improve BEVs' efficiency and driving range. Even though consumers give more significance to real-world driving range than labeled driving range, type approval driving range is also important because it is the standard to compare different types of BEVs in same conditions.

The objective of this paper is to identify the technical attributes of vehicle, battery and motor that impact type approval driving range of BEVs. Multiple linear regression analysis have been conducted in this research paper to evaluate the significance of the attributes in driving range of BEVs. Ratio variables of vehicle weight, battery capacity, motor power and on-board charger power are concluded to have a significant impact on BEVs driving range through the analysis.

Keywords: BEV (battery electric vehicle), electric drive, motor, thermal management, battery management

1 Introduction

The marketability of BEVs will be a more important issue than ever as government authorities plan to phase out subsidies on BEVs, while more and more BEVs are sold around the world. High price of BEVs compared with internal combustion engine vehicles (ICEV), long recharging time and more importantly short driving range are pointed out as obstacles to jump over chasm [1, 2, 3]. Automakers continue to offer and sell BEVs with longer driving range and fast charging capability to enhance the marketability. [2] Especially, academic literatures suggest that driving range is a potential barrier for the market uptake of BEVs [4]. Majority of the BEVs sold in the market currently offers below 200 miles driving range, which is constrained by battery capacity and vehicle curb weight based on labels approved by EPA. In comparison, gasoline ICEVs offer driving range of more than 300 miles per refueling [5].

There are many methods that automakers can employ to address consumers' anxiety about driving range of BEVs. Battery capacity increase is the most accessible and feasible approach to achieve this objective; most car makers are adopting this strategy at the battery pack level. Energy density evolution is ongoing at cell makers through using high voltage technology and injecting more cobalt into chemistry. For instance, Nissan Leaf, Volkswagen e-Golf, Chevrolet Volt, and BMW i3 models have achieved 20~50% increase of driving range [6, 7, 8, 9, 10]. Decreasing charging time is another method to relieve drivers' anxiety. BEV energy efficiency improvement also results in extending driving distance—a 14% increase was observed in Nissan Leaf 2013 model compared to 2012 model by refined aerodynamics, greater utilization of regenerative braking, and better energy management [11].

Consumers' anxiety on driving range is more relevant with real-world driving range, whereas only type approval driving range is available officially for them. BEVs' real-world driving range values tend to be substantially shorter than their type approval values [12]. For instance, consumer-adjusted electric driving range is typically 30% shorter than the tested ranges reported in the United States [13]. The type approval driving range of EVs is estimated under a series of standardized driving tests; these values often differ from real-world driving range values due to many factors, including traffic conditions. Traffic can be significantly different on different routes and locations during peak and lull periods; therefore, the test results from standardized driving cycles are usually inconsistent with the results obtained during real-world driving [13]. Therefore, to provide consumer with information about energy efficiency and emissions, many academic and empirical researches focus on BEV's real-world driving range, which is the most critical factor for adoption of BEVs [14, 15, 16, 17]. On the other hand, the real-world driving range cannot be accurately estimated currently because of differing driving conditions. In this regard, type approval driving range is important because this is the standard to compare different types of BEVs in the same boundary and initial conditions. Furthermore, market researchers and R&D practitioners need to have an understanding on the type approval driving range as well as real-world driving range numbers to promote their BEVs. In spite of the importance of type approval driving range, not much interest has been shown on data-based empirical analysis of the significant factors influencing type approval driving range.

The objective of this paper is to identify the technical attributes of BEVs, battery and motor that impact BEV's type approval driving range. Statistical equation is developed to elaborate the significance of the attributes in the driving range by employing multiple linear regression analysis. Plug-in hybrid vehicles are not included in this study because all of representative test cycles are taking ICEV's engine characteristics as important determinants as well as stored electric energy supplied to the wheels.

The aim of this study is to provide industry practitioners with a comprehensive understanding on the influential factors that affect driving range of BEVs.

2 Literature survey

There are two types of literatures in terms of analysis of parameters influencing BEVs driving range. One is to simulate various factors to estimate the optimal BEV driving range [18, 19, 20, 21, 22, 23]. The other is empirical studies to examine how much the driving range is impacted by different driving conditions with real-world driving data [24, 25].

Understanding key impact factors on the energy efficiency of BEVs which can be interpreted to electric driving range is essential to conduct this study. There are four main categories and those are technology and vehicle characteristics, driver's behavior, travel types and other driving conditions [3]. In type approval process, the latter three are formulated by boundary conditions. Therefore, the technology and vehicle factors are taken into the research consideration. Table 1 represents the only vehicle and technology factors effect on driving range of BEVs in summarizing six prior researches.

After reviewing existing researches on driving range of BEVs and from discussions with industry market researchers and engineers, Table 2 lists the factors taken in this paper for multi-regression analysis. All electric vehicle range is the single independent variable whereas other 10 factors are explanatory variables. As concluded in the prior researches, vehicle weight is the most significant factor influencing driving distance and vehicle cross section area is selected as a substitutional variable for vehicle drag coefficient. Despite no selection from the prior researches, vehicle body type and segment are included in order to examine the effect of the factors in a statistics model. As for technological factors of BEV's components, motor power and torque, battery capacity, cooling system type, battery management system types and on-board charger output power are taken for the analysis considering the significance described in prior researches as shown in Table 2.

Table 1. Influential factors researched in prior researches

Study	Method	Influential factors of technology and vehicle attributes
[18]	Simulation	Vehicle weight, battery capacity, battery weight, body shape, motor power
[20]	Simulation	Vehicle weight, vehicle drag coefficient, vehicle regenerative braking, wheel radius, wheel rolling resistance, battery capacity, battery power
[22]	Simulation	Vehicle weight, motor power, on-board charger power, battery capacity
[26]	Simulation	Vehicle weight, vehicle drag coefficient, vehicle final gear ratio, vehicle max speed, vehicle 0-100km seconds, vehicle cross section area, battery Voltage, battery capacity, motor power, motor torque, motor type, motor efficiency, motor number of poles, moment of inertia, wheel radius, gear efficiency, HVAC power
[28]	Real driving	Vehicle weight, vehicle drag coefficient, vehicle cross section area, wheel radius, wheel rolling resistance, battery capacity, battery voltage, inverter power, motor power, motor torque, wheel speed, wheel torque
[25]	Real driving	Vehicle weight, vehicle drag coefficient, vehicle cross section area, wheel rolling resistance,

Table 2. Factors taken into account in present paper and the source

Factor	Variable	Description	Source
V_Range	Ratio	Vehicle electric driving range*	IHS Markit Fuel Consumption Research
V_Weight	Ratio	Vehicle curb weight	IHS Markit Fuel Consumption Research
V_Area	Ratio	Vehicle cross section area	IHS Markit Fuel Consumption Research
V_Body	Nominal	Vehicle bodytype	IHS Markit Auto Insight
V_Segment	Nominal	Vehicle sales segment	IHS Markit Auto Insight
Mt_Power	Ratio	Motor peak power	IHS Markit Alternative Propulsion
Mt_Torue	Ratio	Motor peak torque	IHS Markit Alternative Propulsion
B_Capacity	Ratio	Battery pack capacity	IHS Markit Alternative Propulsion
B_Cooling	Nominal	Battery cooling system type (Refrigerant, Coolant, Air)	IHS Markit Supplier Insight
B_BMS	Nominal	Battery management system type (Stand alone, Integrated, Modular)	IHS Markit Supplier Insight
OBC_Power	Ratio	On-board charger output power	IHS Markit Supplier Insight

* All different type approval electric driving range values converted into the Worldwide Harmonized Light Vehicle Test Procedure (WLTP) based numbers. BEV's driving range differs relying on Type Approval (TA) tests in different regions as well as parameters of an electric vehicle like battery capacity, vehicle weight, battery management system, thermal management system, electric motor specification and other non-trivial factors. However, market intelligence researchers need standardized criteria to compare different vehicles under the same conditions. It is difficult to compare type approval electric driving range of BEVs sold in different regions under the same conditions, because the value of EVs varies depending on the type approval test cycles. In order to solve this problem, we used a numerical conversion method developed by IHS Markit to compare the different type approval driving ranges.

3 Statistical analysis

Multiple linear regression analysis is conducted to study the significance of the influences. In section 3.1, scope and source of data are introduced and statistical model along with the result is described in the section 3.2. SPSS 25 software of IBM is used for the analysis.

3.1 Data collection

It is not easy to collect comprehensive data of BEVs sold around the globe because of lack of availability of such data in non-commercial sources. However, a few commercial sources provide the data and data from IHS Markit has been used for this study. IHS Markit provides various types of products such as Auto Insight involving specification of all types of vehicles in production, VPaC developed to provide powertrain specification, Alternative Propulsion including eco-friendly car's specification, and Supplier Insight, which offers technology and specification of vehicle components and forecast. The dataset is extracted from the IHS Markit products described in Table 2. and used for this analysis. The dataset includes 266 models sold around the globe. Production of some models discontinued and majority of the cars are in production. Table 3 lists three models out of the dataset as examples.

Table 3. Example of vehicle specification collected in the dataset

	BMW i3	Chevrolet Bolt	Renault Zoe
V_Range (km)	312	520	175
V_Weight (kg)	1,297	1,624	1,427
V_Area (cm^2)	2,799	2,815	2,702
V_Body	Hatchback	Hatchback	Hatchback
V_Segment	C	B	B
Mt_Power (kw)	125	150	57
Mt_Torue (N.m)	250	361	210
B_Capacity (kWh)	33.2	60	22
B_Cooling	Refrigerant	Coolant	Forced Air
B_BMS	Modular	Integrated	Modular
OBC_Power (kw)	11	11	7.4

3.2 Statistical model and result

A multiple linear regression (MLR) is applied to estimate all-electric driving range. As described in Table 3, the seven variables are ratio variables so that those can be used for MLR as it is. Meanwhile other four nominal variables need to be treated as dummy variables because MLR cannot estimate the result with nominal variables. Therefore, this analysis starts with ratio variables to estimate coefficients of the variables and then the nominal variables will be taken into the model one by one as a dummy variable.

To start with ratio variables, backward elimination method is used to test the deletion of each variable using the statistical model fit criterion, delete the variable whose loss gives the most statistically trivial deterioration, and repeat the same procedure until no further variables can be eliminated without a significant loss of fit.

Six independent variables are taken into the model and the particular form of regression function is:

$$\begin{aligned}\mathrm{V\_Range_i} &= \beta_0 + \beta_1 * V\_Weight_i + \beta_2 * V\_Area_i + \beta_3 * Mt\_Power_i + \beta_4 * Mt\_Torque_i \\ &+ \beta_5 * B\_Capacity_i + \beta_6 * OBC\_Power_i + \mathrm{u_i}\end{aligned} \tag{1}$$

where i = 1, 2, …, N represents each vehicle and u_i is the error term for each model. The parameters β_1, β_2, β_3, β_4, β_5, and β_6 represent the estimates with respect to vehicle weight, vehicle cross section area, motor power, motor torque, battery capacity and on-board charger power that be described in Table 2.

As a result of the backward elimination, motor torque turns out to be not influential without losing significance of the model fit. Therefore, the final regression function become:

$$\text{V\_Range}_i = \beta_0 + \beta_1 * V\_Weight_i + \beta_2 * V\_Area_i + \beta_3 * Mt\_Power_i + \beta_4 * B\_Capacity_i + \beta_5 * OBC\_Power_i + u_i \quad (2)$$

The descriptive statistics information of influential factors data is presented in Table 4. The average driving range of 266 models with 36 kWh battery capacity in average is 231 km. The average weighs 1,503 kg and the car is propelled by 92 kw motor. The BEV is capable of 5.8 kw on-board charger power in average.

Table 4. Descriptive statistics

	Mean	Std. Deviation	N
V_Range	231	117.9	266
B_Capacity	36	20.7	266
V_Weight	1503	452.5	266
Mt_Power	92	68.5	266
OBC_Power	5.8	3.9	266

Table 5, 6, and 7 present the result of MLR model (2). The value of R square in Table 6 is 0.886, and the adjusted R square equals 0.884. The R square values show that 88.6% of the changes of driving range could be explained by the variation in other independent variables, and only 11.4% of the changes are random error. The probability of significance level of the regression equation in Table 5 is 0 that is less than the significance level of 0.05. This implicates that the linear relationship between driving range and the four independent variables is significant.

Table 5. Variance analysis

	Sum of Squares	df	Mean Square	F	Significance
Regression	4366710	4	1091677	508	.000
Residual	561036	261	2149		
Total	4927747	265			

Table 6. Model Summary

R	R Square	Adjusted R Square	Standard Error
.941	.886	.884	46.36

Table 7. Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B*	Std. Error	Beta*			Tolerance	VIF
(Constant)	150	10.79		10.00	0.000		
B_Capacity	8	0.24	1.0	22.97	0.000	0.25	4.01
V_Weight	-0.1	0.01	-0.4	-7.85	0.000	0.43	2.34
Mt_Power	0.5	0.06	0.1	2.76	0.006	0.32	3.13
OBC_Power	5	0.89	0.2	3.95	0.000	0.59	1.70

* Coefficient values are modified due to confidentiality keeping the tendency

In a MLR modelling, dummy variables are created to trick the regression algorithm into correctly analysing nominal variables [27]. The equation (3) is an example to make three dummy variables to take four different types of battery cooling system into the MLR model. The value of B_Cooling_i, where i = Refrigerant, Coolant, Air, are "0" or "1". With this modelling, the impact and significance of nominal variables can be obtained.

$$\mathrm{V\_Range_i} = \beta_0 + \beta_1 * V\_Weight_i + \beta_2 * Mt\_Power_i + +\beta_3 * B\_Capacity_i + \beta_4 * OBC\_Power_i \\ +\beta_5 * B\_Cooling\_Ref_i + \beta_6 * B\_Cooling\_Coolant_i + \beta_7 * B\_Cooling\_Air_i + \mathrm{u_i} \quad (3)$$

Table 8. Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B*	Std. Error	Beta*			Tolerance	VIF
(Constant)	150	10.997		8.969	0.000		
B_Capacity	8	0.223	1.04	26.711	0.000	0.292	3.420
V_Weight	-0.1	0.009	-0.23	-7.433	0.000	0.436	2.296
Mt_Power	0.5	0.06	0.10	2.76	0.006	0.32	3.13
OBC_Power	5	0.95	0.10	3.54	0.000	0.52	1.91
B_Cooling_Air	11.3	0.89	0.20	3.95	0.000	0.59	1.70
B_Cooling_Coolant	17.5	7.28	0.01	0.24	0.811	0.62	1.59
B_Cooling_Ref.	30.4	16.95	0.04	1.79	0.074	0.79	1.26

* Coefficient values are modified due to confidentiality keeping the tendency

The value of R square of Equation (3) is 0.885, and the adjusted R square equals 0.882. The probability of significance level of the regression equation is 0. However, significance of battery cooling dummy variables in Table 8 are 0.0, 0.8 and 0.07. The value 0.8 is too big to be statistically significant. Therefore, the classification of battery cooling type turns out to be not valid in a statistics model.

The same analysis carried out to all other norminal variables that are vehicle body type, vehicle segment and battery management system. However, there is no significant statistics models because of one or more dummy variables with high significance values.

4 Conclusion and discussion

This research is motivated by the idea that data based statistical analysis would provide market researchers and eningeers with insights into the vehicle and technology factors that affect BEV driving range.

The results in Table 5~7 show that the independent variables obtained by the proposed multiple linear regression model represent the dependent variable, the electric driving range, with about 90% of explanatory power. As evidenced in many prior researches, introduced in Table 1, battery capacity, vehicle weight and motor power are the most meaningful variables to explain the driving range variances.

The interesting result from the statistics model (1) is that on-board charger power has high relevance with the driving range. There is a high possibility that higher power on-board chargers are more efficient when charging BEVs, that definitely results in longer driving range in type approval procedures. However, from discussion with industry experts, we realized that BEVs with large battery capacity would have high power on-board charger to recharge the battery in a short time. In this case, the collinearity among independent variables need to be checked. However, VIF numbers that are far lower than 10 in Table 8 indicate no significant collinearity issues in a statistics point of view. Therefore, we concluded that on-board charger power can be an influential factor for this model. Furthermore, R square value of the equation involving on-board charger is 0.08 higher than the model without on-board charger power.

Unlike the insistence of strong correlation between electric driving range and market segment [29], the regression models including dummy variables of vehicle body type and segment showed high significance numbers supporting null hypothesis. Not enough sample vehicle numbers in specific segments might result in this high significance values.

In regard to the technology types such as battery management system and cooling system, we expected that there will be high relevance with driving range as prior studies deal with this topic importantly [29, 30]. According to the interview with an industry expert, although the battery management system architecture is used as an independent variable in this study, he suggested that software algorithm is a more important factor than hardware architecture. It is considerable to take a variable related to algorithms in a future research. On the other hand, MLR model involving cooling system architecture dummy variable shows meaningful coefficient in Table 8. The result shows that refrigerant is the most effective and coolant and air-cooling system follow. This tendency was also supported by an interview. However, the analysis significance doesn't support the statistics analysis unfortunately. We intuitively assume that high energy consuming BEVs are equipped with coolant and refrigerant system and this might increase the ambiguity.

In conclusion, four ratio variables are found to have a significant impact on BEVs driving range through the multiple linear regression analysis while other categorical factors are trivial. Nevertheless, the trivial factors in this research are worth researching in future with more relevant values and more sample data.

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Authors

Dr. Seiho Kim is a principal research analyst working at Supply Chain and Technology of IHS Markit. His responsibility includes e-mobility components technology forecasting and he has a specialty in e-mobility batteries. He majored in mechanical engineering and completed the master and doctorate courses in management of technology. His academic interests lie in technology forecasting and technology innovation in automotive industry.

Dr. Jaesik Lee is an adjunct professor in Graduate School of Management of Intellectual Property at Korea University and also Director of Technology Apprisal Department at Korea Technology Finance Corporation. His areas of research interest include innovation financing, technology valuation and technology commercialization.

Dr. Jaejin Kim is a professor in College of Engineering at Yonsei University. His academic interests lie in intellectual property protection, innovation financing, technology valuation and technology commercialization.