ETM
ENGINEERING & TECHNOLOGY MANAGEMENT

Technology Forecasting: Electric Vehicle Batteries

TEAM
MimieAbdulai
Kevin van Blommestein
Elizabeth Gibson
YongwenGu

December 13th, 2013
ETM 532 - Technology Forecasting
Fall 2013
Portland State University

ETM OFFICE USE ONLY
Report No.:
Type:
Note:

Table of Contents

Abstract

Electric Vehicles (EVs) have been introduced into the market for almost a century and are now gaining more attention due to regulations and environmental concerns. However EVs have not yet become mainstreamdue to theshort trip ranges, long charging times, high costs, and poor durability of batteries. In an effort to encourage consumers to purchase EVs, the government has been funding research to solve some of these problems. Specifically, government has been heavily investing in Research and Development (R&D) of EV battery technologies with a wide variety of battery chemistries. The battery technologies were evaluated using data mining to identify leading countries, key research organizations, and current technology emphasis for each R&D stage. In this study, a few technical characteristics of batteries were considered, including specific energy, specific power, and cost to forecast the technological progress in relation to the Department of Energy (DOE)goals for EVs. Due to the lack of required technical characteristics for battery technologies, alternative performance data for EVs were collected, including Miles Per Gallon equivalent (MPGe), acceleration, battery weight, and EV price. For this paper, Technology Forecasting Using Data Envelopment Analysis (TFDEA) was used to forecast future battery performance characteristics.The results were compared against the performance goals established by the DOE. This study showed that the current advancements in EV battery technologies would not meet the DOE requirement with respects to EV range, due to a low average Rate of Change (RoC). Therefore,a new technology must be developed that will increase the current rate of technological advancement.

1 Introduction

Electric Vehicle (EV) battery research isincreasing as environmental concerns receive more political attention. The Internal Combustion Engine (ICE) has been the standard engine in most personal transportation vehicles for most of the world's population for the last century. EVs are gaining popularity as more stringent regulations and cost incentives are being introduced by governments to reduce CO2 emissions produced by the ICEs. Today, while most vehicle manufacturers have a stake in the EV market, the EV has not yet been accepted by the mainstream population as their vehicle of choice. The high cost, limited driving range, charging times and vehicle performance are some barriers adding to the reluctance of wide market adoption[1][2][3].

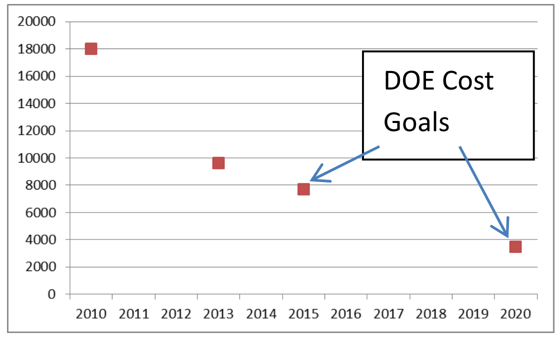
EVs will remain cost prohibitive until there is a significant drop in battery prices. A reporter from the Wall Street Journal quoted Ford's CEO as stating the price of the battery for an EV to be about one third the cost of the vehicle[4]. Many researchers have been working on battery technology to find solutions to the cost problem. Researchers at Argonne labs have been challenged through a Department Of Energy (DOE) funded grant to develop a battery by 2014 with a maximum price of $3,400[5]. A content review of the EV and battery literature was performed to understand the cost concerns of batteries. Cost estimates available in the literature varied widely and relied on a wide range of different assumptions [6]. Furthermore, the development of batteries is a strategic niche for a number of car manufacturers so secrecy is employed to keep detailed data confidential [6][7]. Therefore, there are few empirical studies attempting to forecast the research progress of this key component in relation to the cost goals required for broad market acceptance. This study will use a forecasting method to understand if the EV battery technology is on track to meet the targeted goals established by the Department of Energy (DOE) within the next 10 years.

1.1 Electric Vehicles (EVs)

EVs are not new. In fact, in the early 1900s the ratio of EVs was almost double that of gasoline powered cars[8]. Wealthy individuals enjoyed the electric start and typically lived in town driving short distances on improved roads. Innovations in manufacturing with the assembly line reduced the cost barrier making vehicles feasible for the mass market. Further technology innovations such as the electric starter and improved roads helped to fuel the automotive industry. Consumers became increasingly concerned about short trip range, long charging times and poor durability of electric batteries.The ICE vehicles soon became the vehicle of choice because they performed better and cost less. Today, these concerns remain and must be solved for the consumer market to accept an EV as an ICE vehicle substitute. Government has recognized these concerns and the DOE has issued over $2 billion in grants to accelerate research efforts[9].Researchers have documented that by 2020 "*more than half of new vehicle sales will likely be EV models*"[8]. However, to meet this goal battery technology must improve while reducing the cost.Industry analysts estimate the cost of the Nissan Leaf battery pack at $18,000 in 2010 and $12,000 in 2013[10]. While this shows a significant decrease over a three year period.DOE cost targets are specified in $/kWh. In 2010, the DOE estimated the cost of the EV battery to range between $700-$950/kWh[9] with a target of $300/kWh by 2015 and $150/kWh by 2020. In 2010, the Nissan battery was estimated to cost $18,000 for a 24kWh lithium-ion battery[10]. Conversion of the Nissan battery cost into $/kWh calculates to $750/kWh. This figure falls at the bottom of the range reported by the DOE supporting the validity of the number. Using the cost goals established by the DOE for 2015 and 2020 this would translate to a cost estimate for the Nissan Leaf EV battery pack to be about $7,700 in 2015 and more than half that cost by 2020 as shown in Figure 1.

Figure 1: Cost projections for Nissan Leaf EV battery[9]

Year	DOE ($/kWh)	Leaf ($/kWh)	Battery ($)
2010	700-950	750	18,000
2015	300-400	321	7714
2020	150	150	3600



In general, analysts were reporting the cost of the battery to be approximately 50% of the cost of the vehicle in 2010 and about 30% in 2012[4].By removing just the cost savings from the battery from the vehicle price this means a Leaf costing $36,000 in 2010 could cost $24,700 in 2015 without adjusting for inflation. The MSRP was listed at $28,800 in 2013 for this vehicle. Following the rule of thumb that the battery is about a third the cost of the vehicle, the Nissan battery would cost about $9600 as shown in the figure 1 graph.This example shows the 2020 goal may be difficult to achieve. While this theoretical case provides an interesting example, a more scientific method is derived to explore the trend with specific battery technologies.

1.2 Battery Technologies

The EV battery is used to power a controller which runs the electric motor. It contains two electrodes, a cathode and an anode. In general, a separator creates a barrier between the electrodes to prevent them from touching while allowing electrical charge to flow between them. Electrolyte allows the electric charge to flow between the cathode and anode. Researchers are aggressively exploring improvements in each of these technologies. A variety of chemistries are used by different battery developers to power EVs today. The literature was searched to determine differences between general types of battery chemistries in relation to common attributes. Table 1compares different battery chemistries with common attributes.

Table 1: Comparison Between Battery Types[8][11][12][13][14]

Attribute	Lead Acid	NiMH	Li-Ion	Molten Salt	Metal-air

Weight (kg)	Poor	Fair	Good	Fair	Good
Volume (lit)	Poor	Good	Good	Good	Good
Capacity/Energy (kWh)	Poor	Fair	Good	Fair	Good
Discharge Power (kW)	Good	Fair	Good	Good	Fair
Regen Power (kW)	Poor	Fair	Good	Good	Good
Cold-Temperature (kWh & kW)	Good	Fair	Poor	Poor	Fair
Shallow Cycle Life (number)	Fair	Good	Good	Good	Poor
Deep Cycle Life (number)	Poor	Good	Fair	Good	Poor
Calendar Life (years)	Poor	Fair	Fair	Good	Poor
Cost ($/kW or $/kWh)	Good	Poor	Poor	Good	Poor
Safety- Abuse Tolerance	Good	Good	Fair	Poor	Poor
Maturity – Technology	Good	Good	Fair	Fair	Poor
Maturity – Manufacturing	Good	Fair	Good	Good	Fair

1.2.1 Specific power and energy

EV batteries are typically characterized by a power-to-weight ratio (specific power) andanenergy-to-weight ratio (specific energy or energy density).The power-to-weight ratio, also referred to as specific power, is a common attribute to measure actual performance of an engine or performance of a vehicle. This measure can be inconsistently quoted because manufacturers will often use the peak value and researchers may quote the actual value as measured in a laboratory or field test. The tradeoff for batteries is between specific energy and specific power[11].If specific power reaches high values, the specific energy starts to decrease. A balance therefore needs to be maintained between specific energy and specific power. Since the acceleration of a vehicle is associated with specific power, and the range of a vehicle is associated with specific energy, the tradeoff is also between acceleration and range.While batteries are present in HEVs, Plug-in HEVs (PHEVs), as well as full EVs,each have their own requirements. For a HEV, the requirement of the battery is not necessarily to add range to the vehicle but rather to aid in the acceleration of the vehicle. Therefore the specific energy will be low, while the specific power will be high. For an EV, the requirements are both, since the battery is aiding in acceleration and range. However if the specific power is too high, then the range will be low so a balance needs to be reached. Additionally, cooling requirements for larger batteries in EVs will contribute to the weight of the battery more than smaller batteries in HEVs.

1.2.2 Battery Research and Development (R&D)

The Office of Energy Efficiency and Renewable Energy (EERE) has been chartered to advance "*the development of batteries and other energy storage devices to enable a large market penetration of hybrid and electric vehicles*"[15]. In 2010, they released funding with established performance targets as reflected in Table 1.

Table 1: DOE Battery Performance Targets

Energy Storage Goals	HEV (2010)	PHEV (2015)	EV (2020)
Equivalent Elect Range (miles)	N/A	10-40	300
Discharge Pulse Power (kW)	25	28-50	80
Regen Pulse Power (10 sec) (kW)	20	25-30	40
Recharge Rate (kW)	N/A	1.4-2.8	5-10
Available Energy (kWh)	0.3	3.5-11.6	30-40
Cycle Life (cycles)	3000	3,000 – 5,000 deep discharge	1500 deep discharge
Calendar Life (year)	15	10+	10
Maximum System Weight (kg)	40	60-120	133
Operating Temp Range (ºC)	-30 to +52	-30 to 52	-40 to 85

Research funded a wide variety of battery chemistries. Through a public bid process, twelve proposals were selected for evaluation for grants. Upon results of this work, four laboratory facilities were established with the help of DOE grants.Table 2reflects the laboratory facilities established as a result of this funding research.

Table 2: Battery Development Contracts

Laboratory	DOE Grant	Facility Description
Argonne National Lab	$8.8 M	Battery Prototype Cell Fabrication, Materials Production Scale-up, Post-test Analysis
INL: Idaho National Lab	$5.0 M	High-energy Battery Test Facility
Sandia National Labs	$4.2 M	Battery Abuse Testing Lab
NREL	$2.0 M	Battery Design and Thermal Testing Facility

Sandia labs actively identified major battery research areas as materials, the power cell, the system and commercialization. A synthesis of the final reports from each of the labs listed in Table 2 was performed[16][17][18]. The challenges and goals appear to have been met for HEVs. Specifically, the battery in the Toyota Prius, a nickel metal hydride (NiMH)chemistry, obtains a reported 50 Miles Per Gallon equivalent (MPGe). The outcome of nearly a decade of funding resulted in R&D efforts identifying two broad categories of battery technologies best suited for EVs: lithium-ion (Li-Ion) and nickel-metal hydride (NiMH). The Li-ion chemistries differ in the fact that they represent a family of battery chemistries each with strengths and weaknesses.

1.2.3 Battery Applications (Electric Vehicles)

The results of a literature review on the commercialization of these battery technologies show that they are both used and present in the market. A popular NiMH battery is the Varta and a popular Li-Ion battery is made by Johnston Controls. Table 3shows the current battery components used in certain commercialEVs.

Table 3: Batteries used in EVsand HEVs of selected car manufacturers [8]

Company	Country	Vehicle model	Battery technology
GM	USA	Chevy-Volt Saturn Vue Hybrid	Li-ion NiMH
Ford	USA	Escape, Fusion, MKZ HEV Escape PHEV	NiMH Li-ion
Toyota	Japan	Prius, Lexus	NiMH
Honda	Japan	Civic, Insight	NiMH
Hyundai	South Korea	Sonata	Lithium polymer
Chrysler	USA	Chrysler 200CEV	Li-ion
BMW	Germany	X6 Mini E(2012)	NiMH Li-ion
BYD	China	E6	Li-ion
Daimler Benz	Germany	ML450, S400 Smart EV (2010)	NiMH Li-ion
Mitsubishi	Japan	iMiEV (2010)	Li-ion
Nissan	Japan	Altima Leaf EV (2010)	NiMH Li-ion
Tesla	USA	Roadster (2009)	Li-ion
Think	Norway	Think EV	Li-ion, Sodium/Metal Chloride

As a result of the literature review and synthesis of the national lab results we elected to focus our study on lithium ion (li-ion) and nickel metal hydride (NiMH) EV batteries. In general, the advantage to Li-ion batteries is that they can store more energy per mass and volume than the NiMH because lithium is a lightweight metal and because the properties result in a cell voltage between 3.3V -4.3V compared to about 1.2V for NiMH.

1.2.4 Battery Technical Characteristics

Important technical characteristics of batteries used for EVs were identified. The two main characteristics identified were specific energy and specific power. Specific energy is important because it translates into the range an electric vehicle can travel on a single charge. Specific power is important because it translatesintothe acceleration of an electric vehicle. The following is the list and description of the characteristics identified:

1. **Capacity**: This is defined as the total Watt-hours (Wh) that can be discharged from a fully charged battery. Mathematically, the formula used to determinethis value is as follows (Ah: Ampere-hour) :

Equation used for Capacity (Wh) = Rated Ah Capacity X Rated Battery Voltage

2. **Cost:**This is the cost per kilo Watt hour ($/kWh) for the battery.The following equation calculates the cost using the battery capacity:

   Equation for total cost ($/kWh) = battery cost ($)/ battery capacity (kWh)

   A study released by the USABC [19] has determined that battery technology must reach approximately $200 - $300/kWh to make EVs commercially viable. The cost models consider materials, packaging efficiencies, manufacturing processes, economies of scale and other factors which are beyond the scope of this study.

3. **Specific Energy (Energy Density)**: This is how much energy a battery can store per unit mass. This measure is important because it helps to measure the range and weight impact of the vehicle performance. The units for specific energy is typically Watt-hours per kilogram (Wh/kg). Where necessary, specific energy can be calculated using the following equation:

   Equation used to calculate Specific Energy (Wh/kg) = batterycapacity (Wh) / battery mass (kg).

   Research shows the practical limit for Li-ion technology to be about 300 Wh/kg[19].

4. **Specific Power:** This is the maximum available power per unit mass.

Equation used to calculate Specific Power (W/kg) = battery rated peak power (W) / battery mass (kg).

5. **Cycle Life:**This is the number of discharge-charge cycles the battery can handle before it fails to meet specific performance criteria. The actual operating life of a battery is affected by temperature, charge/discharge rates that results in user variation.

1.2.5 Battery Cost Forecasting

There are three primary cost models used for analyzing battery costs: the United States Advanced Battery Consortium (USABC) model, the Argonne model and the TIAX model[11]. Each of these cost models analyzes process criteria for manufacturing and producing a battery for commercialization. The USABC costs specific battery designs after cell performance is validated. The Argonne model uses a manufacturing optimization model tied to a volume production and sales model. The TIAX model is used to identify factors with the highest cost impact in the manufacturing and distribution process. While each of these models is important to the technology transfer and manufacturing process, none of them forecasts what the cost is likely to be based on forecasting methods. However, they help to identify a common set of criteria.

1.3 Technology Forecasting Methods

1.3.1 Technology Forecasting using Data Envelopment Analysis (TFDEA)

Technology Forecasting using Data Envelopment Analysis is the forecasting method used for in this paper.

“Technology Forecasting Using Data Envelopment Analysis (TFDEA) was introduced in 2001 [20] as an extension of Data Envelopment Analysis (DEA) used in operation research methods. TFDEA is a powerful tool for technology forecasting, risk identification, new product development (NPD) product planning, and early evaluation of disruptive technology”. This is because it “offers effective means to determine technological capability over time without the burden of fixed a-priori weighting schemes”[21]. The basic process of TFDEA is first to determine the scope of the forecast, then define the product, followed by defining the characteristics of the state-of-the-art (SOA), then determining the model, collecting the data, analyzing the technology progress and finally examining the results [22]. One fundamental concept for TFDEA is being SOA technology, which indicates a technology’s superiority over the others for the time being that the analysis is performed. If a technology is SOA, its efficiency score is assigned as 1, by considering the historical levels of performance. Subsequent efficiency scores are then assigned for each of the remaining technologies based on the preceding SOA technology[20].

1.3.2 Regression

Although the method is not included as means of forecasting in the final paper, it was employed to further analyze and make sense of the results of the TFDEA findings.

Regression analysis is one of the most used techniques for analyzing multi factor data. Its broad appeal and usefulness result from the conceptually logical process of using an equation to express the relationship between a variable of interest (the response) and a set of related predictor variables.

Martino (1993) [Miii] explains that “extrapolation(regression) is used to project progress beyond the upper limit of the current technical approach, which growth curves are not suited for this purpose.
For a single technical factor (Performance) we use: $y= a+bt$, where y is performance, and a and b are coefficients of the regression model.
For multiple technical factors we use: $y = a+b1x1+b2x2+b3x3+...$, where y is the year of a technology or product and x1, x2,x3 are the technical parameters influencing overall performance, therefore year of the product. Here, b1,b2,b3 are the coefficients of the multiple regression model.
The general process followed for regression analysis is first to identify what available data best represents the technology of interest, followed by collecting the data, exploring the data and identifying patterns and relationships of interest, creating the regression model, verifying the model, and finally testing the model using validation data.“

2 Methodology

Figure illustrates the methodology that was followed for this study. This first step of the methodology was to understand the different types of technologies that exist and the societal context in which they are being developed, by using data mining. Once there was a good understanding of the environment of these technologies, relevant data was collected that could best explain the technology advancements over time. The data was then analyzed, and the TFDEA inputs and outputs were chosen from this datathat could best explain the technologies. The results of the TFDEA model were then analyzed, and if required new data was collected or the model was updated. Based on the results, a conclusion was made and possible implications were mentioned from the advancements of this technology.

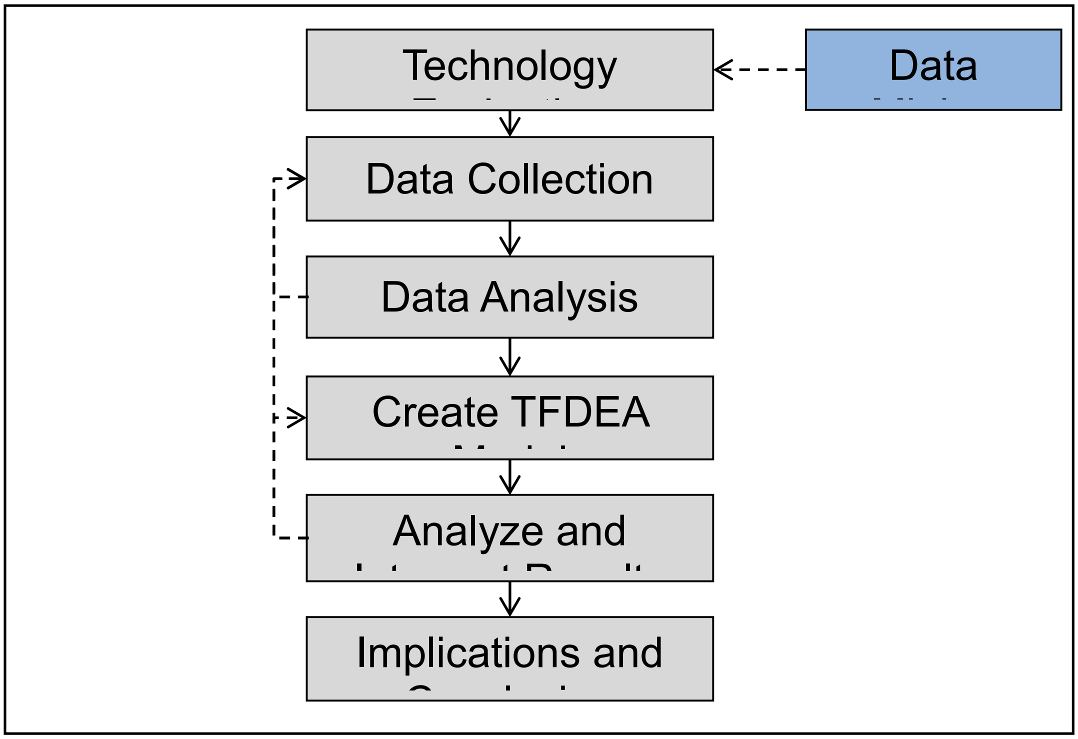


Figure 2: Research Methodology

3 Technology Evaluation

3.1 Data Mining

Martino [23] describes the association between the different R&D stages and typical sources of information, as shown in Table 4. The first four sources were used in order to evaluate the current status of EV battery technologies. The databases used for each of these stages are also illustrated in Table 4. The information gathered from the data mining process was used to create a Technology Delivery System (TDS), representing the societal context in which the technology is being developed.

Table 4: Typical source of R&D stage information[23]

R&D Stage	Typical Source	Database
Basic Research	Science Citation Index	Web of Science
Applied Research	Engineering Index	Compendex/INSPEC
Development	Patents	USPTO, JPO, EPO, WIPO

Application	Newspaper Abstracts Daily	LexisNexis
Social Impacts	Business and Popular Press	-

3.1.1 Search Methodology

Keywords were identified during the literature review for each EVbattery technology and a Boolean search query was created, asshown in Table 5.The battery type was used as the keyword in the article and patenttitles, while *electric vehicle* was used as the keyword in the entire article. The idea was to capture articles and patents mainly focusing on the respective technologies by focusing on the titles of the articles and patents. Each of the databases mentioned above were searched using the Boolean search query.

Table 5: Boolean Search Strings

Battery Technology	Boolean SearchQuery (All under Title of document)
Lead-acid	*TTL:((batter*) **AND** ((lead acid) **OR** (Pb acid)))**AND**(electric* vehicle)*
NiMH	*TTL:((batter*) **AND** ((NiMH) **OR** (Nickel Metal Hydride))) **AND**(electric* vehicle)*
Li-Ion	*TTL:((batter*) **AND** ((Li ion) **OR** (Lithium Ion))) **AND**(electric* vehicle)*
Molten Salt	*TTL:((batter*) **AND** ((ZEBRA) **OR** (NaNiCl)**OR** (Sodium Nickel Chloride) **OR** (NaS) **OR** (Sodium Sulphur) **OR** (LiS) **OR** (Lithium Sulphur) **OR** (Molten Salt))) **AND**(electric* vehicle)*
Metal Air	*TTL:((batter*) **AND** ((Li air) **OR** (Lithium air)**OR**(Al air) **OR** (Aluminum air)**OR**(Zn air) **OR** (Zinc air)**OR**(Fe air) **OR** (Iron air)**OR** (Silicon air) **OR** (Metal air))) **AND**(electric* vehicle)*

3.1.2 Growth Rates

Figure 1 illustrates the Share of Total Articles or Patents versus the Compound Annual Growth Rate (CAGR) for each EV battery technology under each R&D stage, between 2000 and 2012.The share of total articles or patents is calculated by adding all of the articles or patents up from 2000 until 2012, and calculating the percentage that belongs to each technology. Lithium-ion has the highest CAGR under each category except for basic research. Metal-air has the highest CAGR for basic research, however with a relatively small share of the total scientific articles. Due to the very high theoretical specific energy of some metal-air battery technologies, it is understandable why there would beinterest in this technology.The lead-acid battery technology hasone of the lowest CAGR's for each stage, which is expected due to its low specific energy and phasing out of the technology. Finally, no relevant patents were identified for the molten salt battery technology associated with electric vehicles, however excluding *electric vehicle* from the search query resulted in over 300 patents. The limited application of these batteries to electric vehicles is likely due totheir high operating temperatures.

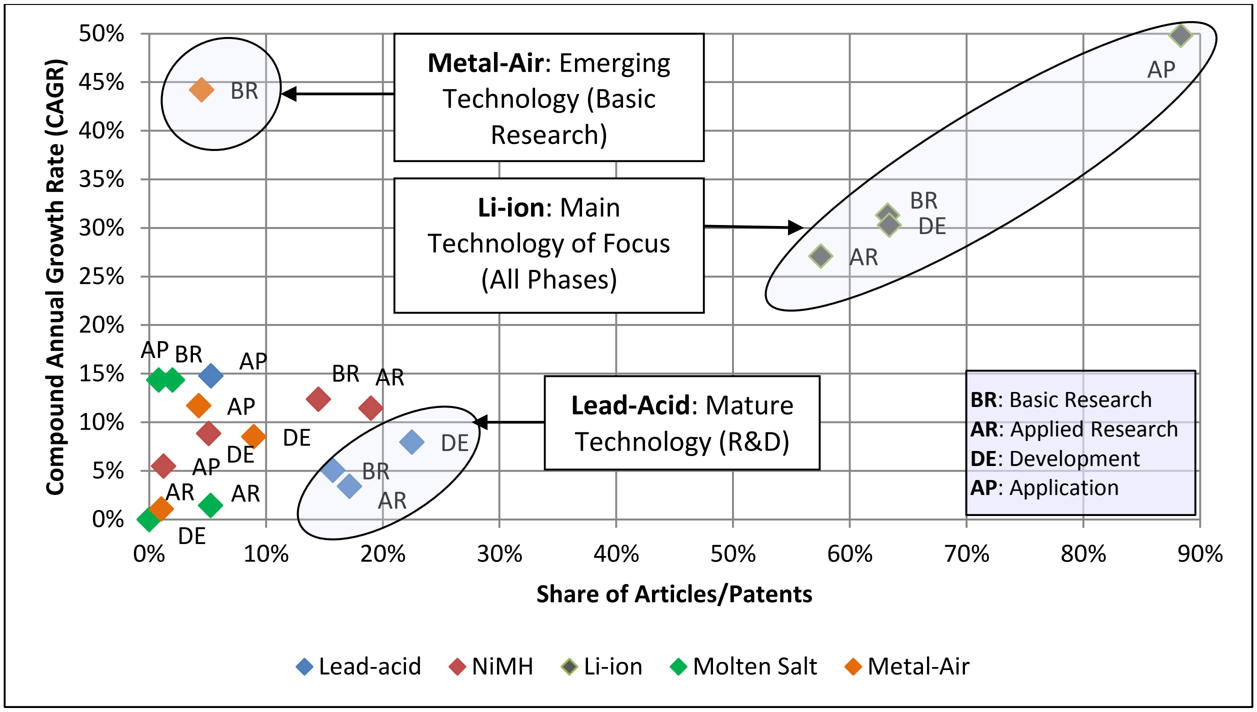


Figure 1: Share of Articles (2000 - 2012) vs. Compound Annual Growth Rate (2000 - 2012)

3.1.3 Leading Countries (Basic and Applied Research)

Table 6illustrates the top 3 countries for each EV battery technology identified from the Web of Science and INSPEC databases. The USA and China were identified in majority of the top 3 countries. The large investments in battery technologies by the USA, South Korea, Japan, and China [24] in Research and Development is a possible explanation for these findings. The USA is the top country in all sections except for applied research in NiMH and lithium-ion battery technologies.

Table 6: Top 3 Countries per Technology (Basic and Applied Research)

Battery Technology	Basic Research	Applied Research
Lead-Acid	USA (35%), England (9%), Germany (8%)	USA (29%), UK (10%), China (9%)
NiMH	USA (28%), Japan (26%), China (11%)	China (42%), USA (30%), Japan (15%)
Li-ion	USA (31%), China (25%), South Korea (12%)	China (34%), USA (29%), Japan (10%)
Molten Salt	USA (26%), England (13%), China (13%)	USA (27%), Germany (19%), UK (16%)
Metal-air	USA (56%), South Korea (18%), China (9%)	USA (39%), Israel (18%), France (12%)

3.1.4 Key Research Organizations (Basic and Applied Research)

For basic research, key organizations were identifiedusing the highest number of publications from the search results.For applied research, the relationship between organizations were evaluated using Social Network Analysis (SNA), due to the higher number of articles identified. The purpose of using SNA is to identify organizations that are influential in specific areas of research, and which organizations are collaborating with one another. A social network consists of nodes (in this case research organizations) and edges connecting these nodes together. If two organizations collaborated on a specific article then they are connected by an edge. The three most basic centrality measurements are [25]:

1. Degree Centrality - The number of direct connections to a node. The higher the number of connections, the higher the number of collaborations between the specific node (organization) and other nodes (organizations),
2. Closeness Centrality - The distance from a specific node to all other nodes. The closer a organization is to all other organizations, the easier it is for that node to monitor what is happening in the network. This value is only meaningful for a connected network,
3. Betweenness Centrality - The number of shortest paths between two nodes that a specific node resides on. The more organizations that depend on a specific organization for connections, the more powerful that organization is.

Table 7 illustrates the top organizations associated with basic and applied research. Research organizations with the highest degree centrality together with the highest betweenness centrality were selected. The intention was to find organizations that collaborate with the most other organizations, and who are critical in connecting organizations together. Due to the low connectivity of the networks, the closeness centrality was not meaningful.The organizations with the highest publications are also listed in Table 7.

Table 7: Top Organizations (Basic and Applied Research)

Battery Technology	Research Organizations
Li-ion **(Basic Research)**	**Pub:** Department of Energy (US),Argonne National Labs (US),Beijing Institute of Technology (CN), University of Chicago (US).
Li-ion **(Applied Research)**	**Deg/Bet:** Beijing Institute of Technology (CN), Peking University (CN), University of Michigan (US), SK Energy Institute of Technology (KR), **Pub:** Beijing Institute of Technology (CN), Korea Advance Institute of Science and Technology (KR), Argonne National Labs (US).
Metal-air **(Basic Research)**	**Pub:** Department of Energy (US),Ulsan National University of Science Technology (KR), Georgia Institute of Technology (US), Argonne National Labs (US),

NiMH (Applied Research)	***Pub:** Ovonic Battery Company (US), Beijing Gen Res Institute for Non-Ferrous Metals (CN), Electro Energy Inc. (US)

*The highest degree centrality measurements were 1; therefore all betweenness centralities were 0.

3.1.5 Key Organizations (Development)

The top assignees (organizations) were identified from the patents for each technology, and are shown in Table 8. The organizations were identified online and it was verified whether their current focus of research and development was on the associated technologies. As an example, Exide Technologies is one of the world's largest producers of lead-acid batteries, and Ovonic Battery Company develops and markets NiMH battery packs for Hybrid Electric Vehicles (HEVs). Additionally, in 2010 Japan and South Korea held an 80% share of global production of advanced Li-ion batteries, which aligns with the fact that almost all top assignees are from Japan [26].

Table 8: Top Organizations (Development)

Battery Technology	Organizations (Assignees)
Lead-Acid	Exide Technologies (US), Matsushita Electric Industrial[1] (JP), GS Yuasa Corp. (JP), Panasonic Corp. (JP), Shin Kobe Electric Machinery Co. (JP), Johnson Controls Inc. (US).
NiMH	Ovonic Battery Co. (US), Chevron (US), Matsushita Electric Industrial[+] (JP), Toyota Motor Corp. (JP), Ceramatec Inc. (US), Sanyo Electric Co. Ltd. (JP).
Li-ion	Hitachi Ltd. (JP), Toyota Motor Co. (JP), Sony Corp. (JP), Nissan Motors (JP), GM Global Technology Operations (US).
Molten Salt	*
Metal-air	Electric Fuel Ltd. (IL),Reveo Inc.(US), Tesla Motors (US), Revolt Tech Ltd. (NO), Nanotek Instruments Inc. (US).

[+] *Now Panasonic Corporation*   **No relevant patents were identified*

3.2 Technology Delivery System (TDS)

Based on the information identified from the data mining process, a Technology Delivery System (TDS), as described by Roper et al. [27],was created.Figure 3 illustrates the TDS for EV battery technologies. The leading countries, key research organizations, and current technology emphasis were all identified from the previous data mining results. Government funding for research and development for the USA, China, Japan, and South Koreawas identified from literature, as well as the positive and negative influences that are promoting or hindering the development and application of the technology. The purpose of creating the TDS is twofold. One reason was to gain a further understanding, beyond the literature, of the environment of the technology. The second reason was to identify the current technology emphasis for each R&D stage, in order to recognize technologies that could potentially disrupt the current EV market.

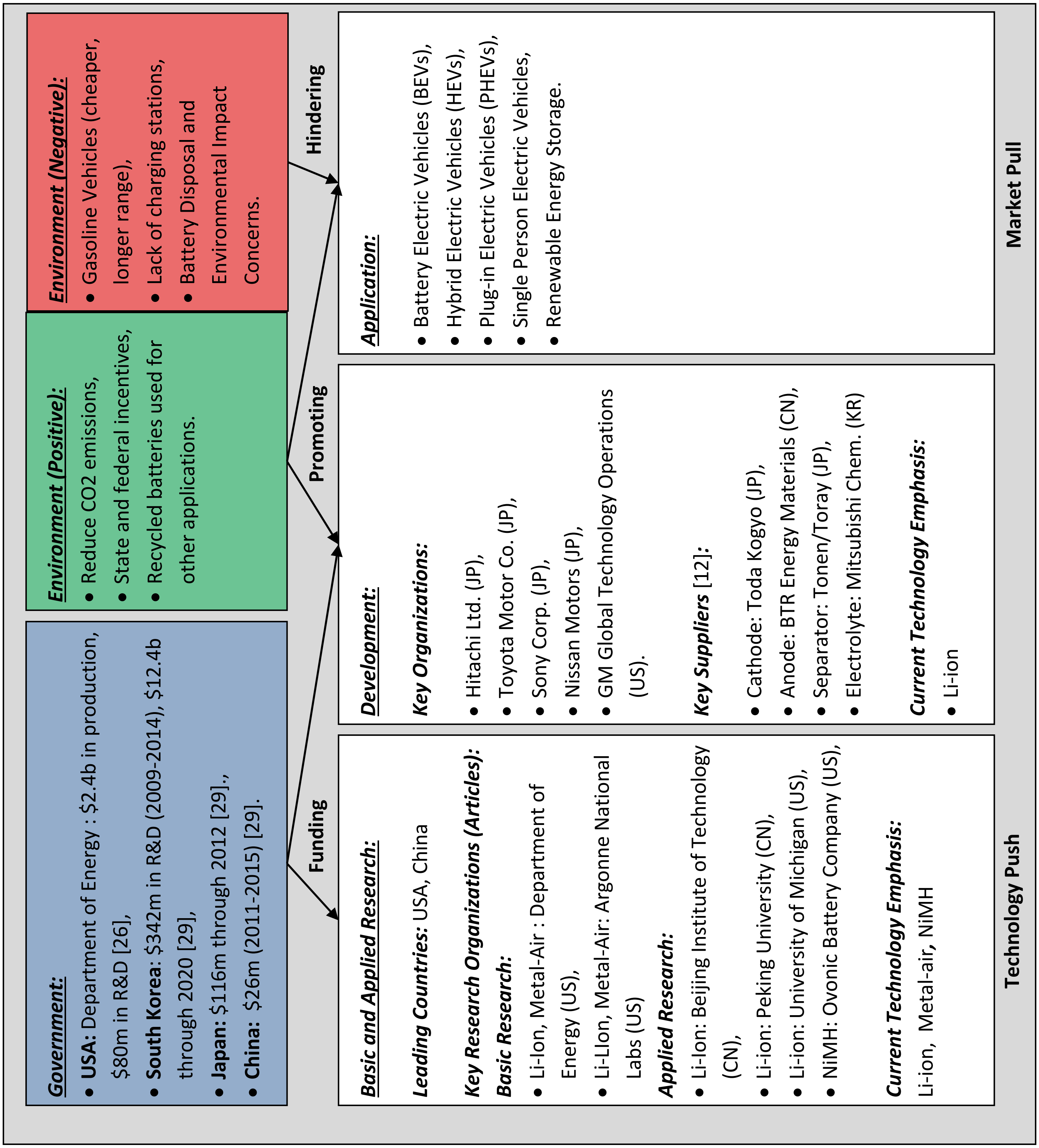


Figure 2: EV Battery Technology Delivery System (TDS)

3.3 Technology Framework

Figure 4illustrates the technology framework. The technical performance relates to the battery technology, while the functional performance relates to the application, EVs. Each material used in the battery technologies has a theoretical specific energy which is the limitation for that material. Additionally, for safety requirements, the temperature and voltage need to be limited below a certain threshold for safety and practicality reasons. The intention of this paper is to forecast battery technologies, as marked in the figure.

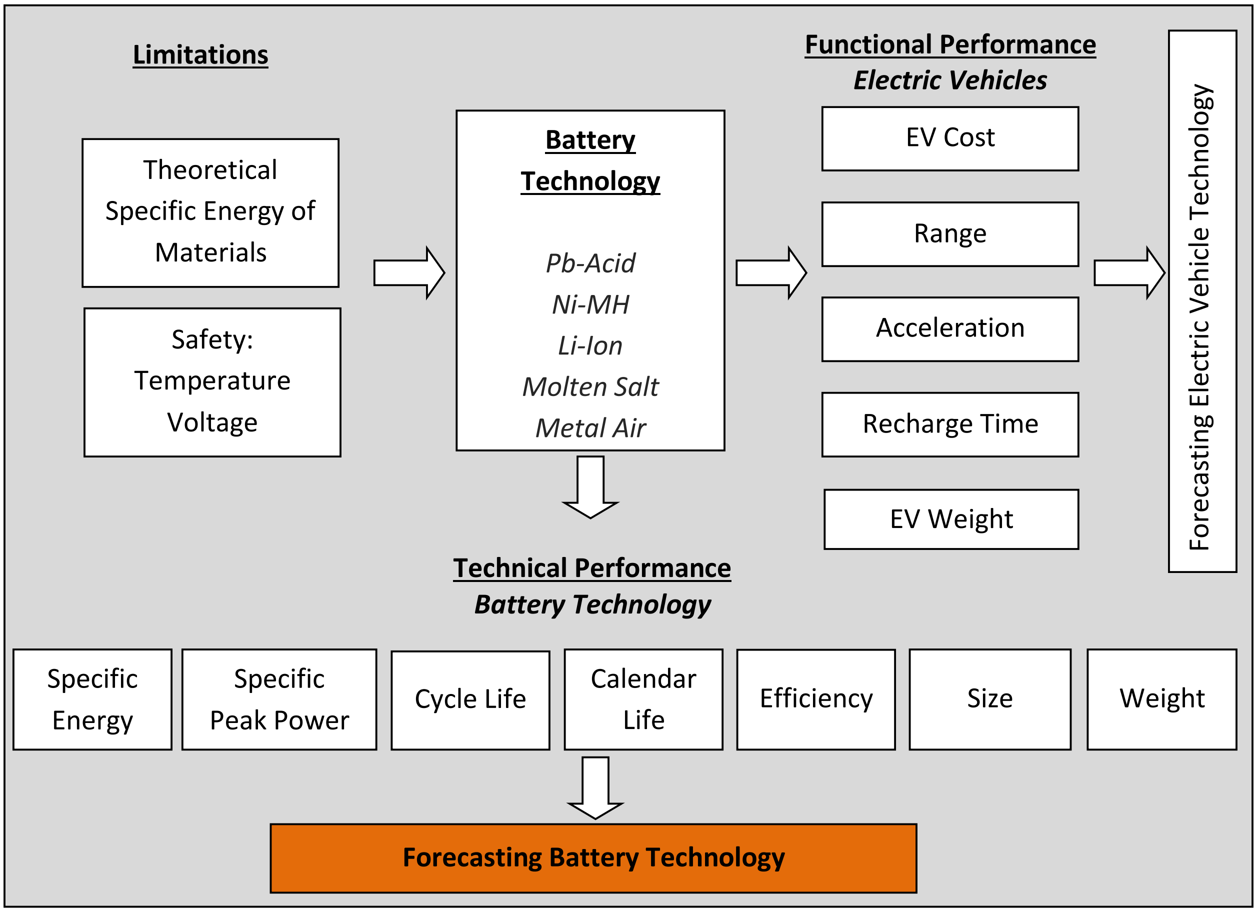


Figure 3: Technology Framework for Battery Technologies

4 Data Collection and Analysis

There were several limitations to this study in terms of data collection.Srinivasan [11]mentions that the tradeoff for battery technologies is between specific energy (Wh/kg) and specific power (W/kg). Higher values of specific power result in a reduction in specific energy. Since range is associated with specific energy and acceleration is associated with specific power, there is also a tradeoff between range and acceleration. There was difficulty collecting specific power and accurate costs for EV batteries, however acceleration and EV cost data were easier to obtain. All the data collected for 26 EVs is illustrated in Table 9.

Table 9: Data Collected

Technical Performance Battery Technology	Functional Performance Electric Vehicles
Specific Energy (Wh/kg)	Release Date
Battery Weight (kg)	Miles Per Gallon equivalent (MPGe)
Total Battery Pack Voltage (V)	Ideal Range (miles)
Battery Ampere Hours (Ah)	Rated Motor Power (kW)
Battery Type	Recharge Time (h)
Battery Energy Capacity (kWh)	Motor Torque (Nm)
	Top Speed (mph)
	2013 Price ($)
	Weight (kg)
	Acceleration (s)

5 Technology Forecasting using Data Envelopment Analysis (TFDEA)

5.1 Input and Output Selection

The initial intention for the TFDEA model was to use the battery weight(kg) and price($) as inputs and battery energycapacity (kWh) and battery peak power(W) as outputs.The reason for these specific parameters was due to all literature measuring the improvements in battery technologies by specific power, specific energy, and price. As mentioned above, battery peak power and accurate battery price data could not be obtained; therefore acceleration and EV price data were selected instead. Since acceleration is associated with battery peak power, it was seen as an acceptable replacement.Additionally, since a large fraction of the EV price is associated with the battery price, this was also seen as an acceptable replacement. However, both acceleration and EV price data take into account other factors of the EV and therefore this is not a completely accurate representation of the battery. This was however the only option available with the data collected.

Since acceleration is a performance characteristic of the EV, it was decided to use another performance characteristic in place of battery energy capacity, namely Miles Per Gallon equivalent (MPGe). By doing so, the same characteristics of the EV are taken into account by both outputs. One MPGe is approximately

0.0292 times the range of the EV in miles divided by the battery energycapacity in kWh. Therefore MPGe takes the range of the EV into account, for a specificbattery energy capacity (kWh).

Battery weight was seen as an important technical characteristic to include in the model, since it is included in both specific power and specific energy. An improvement in the performance of a battery is measured by these values increasing. Since specific energy is equal to battery energy capacity divided by battery weight, Figure 4 shows that the improvement in specific energy over time is not due to increasing battery energy capacity, but rather a reduction in the weight of the battery.

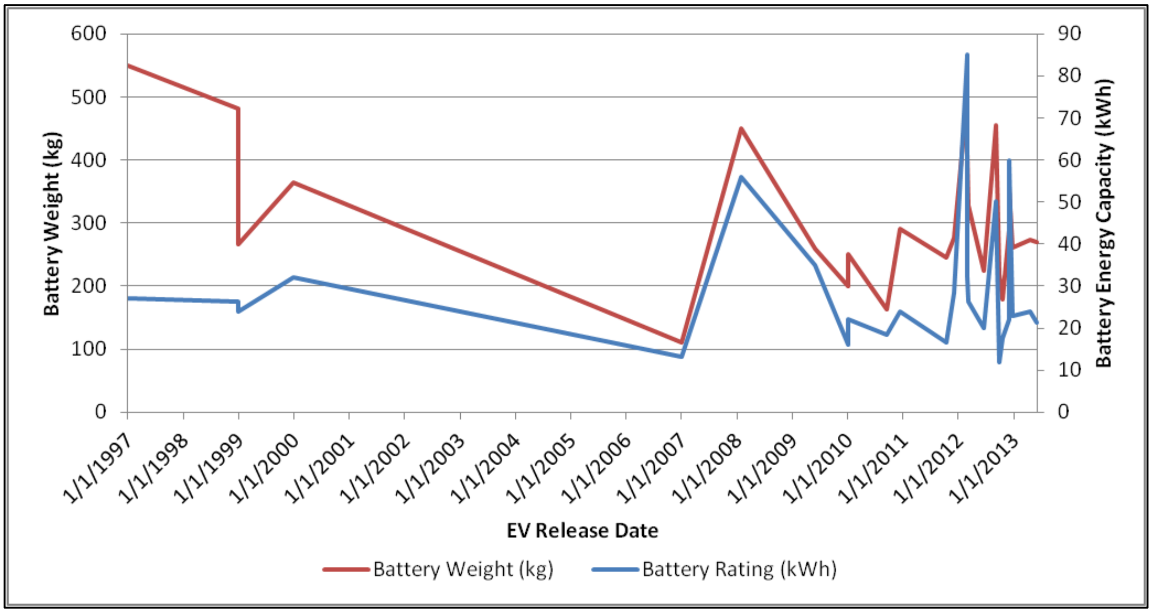


Figure 4: Decreasing Battery Weight over Time

5.2 Model

The final TFDEA model selected is illustrated in Figure 6. The initial idea was to include the EV price as an input, but the intention of the study was to forecast the improvement in the performance of the battery and price over time.Since an output-orientated model was selected, the output was maximized for the given input, battery weight.The question that the model would answer was therefore;for a given battery's weight what improvements would you see in the price, MPGe, and acceleration? It was assumed that the focus on EV battery technologies would be to increase the range and acceleration of the EV while maintaining the same battery weight.

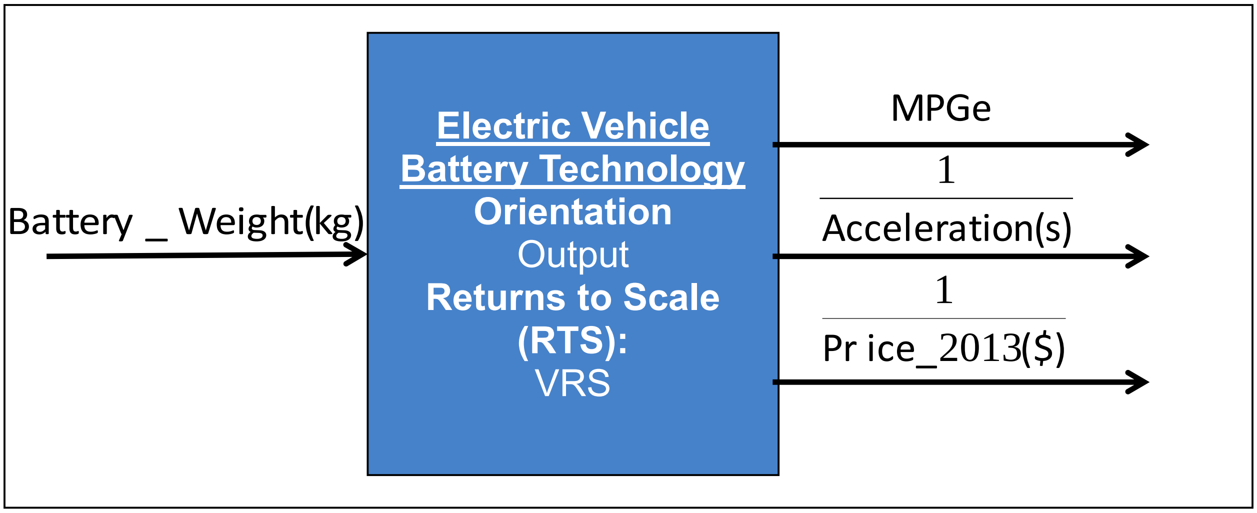


Figure 5: TFDEA Input/Output Model

5.3 Results

The frontier year for the TFDEA model was selected by using 30 percent of the data for validation. The frontier year chosen was 2012.5 (June 2012) and the resulting forecast is shown in Figure 6. The Mean Absolute Deviation (MAD) for the forecast was 0.9296 years, with aaverage Rate of Change (RoC) was 1.03029. Only 5 out of 8 EV batteries forecasted, sincethe other 3 batteries did not have an efficiency greater than 1.

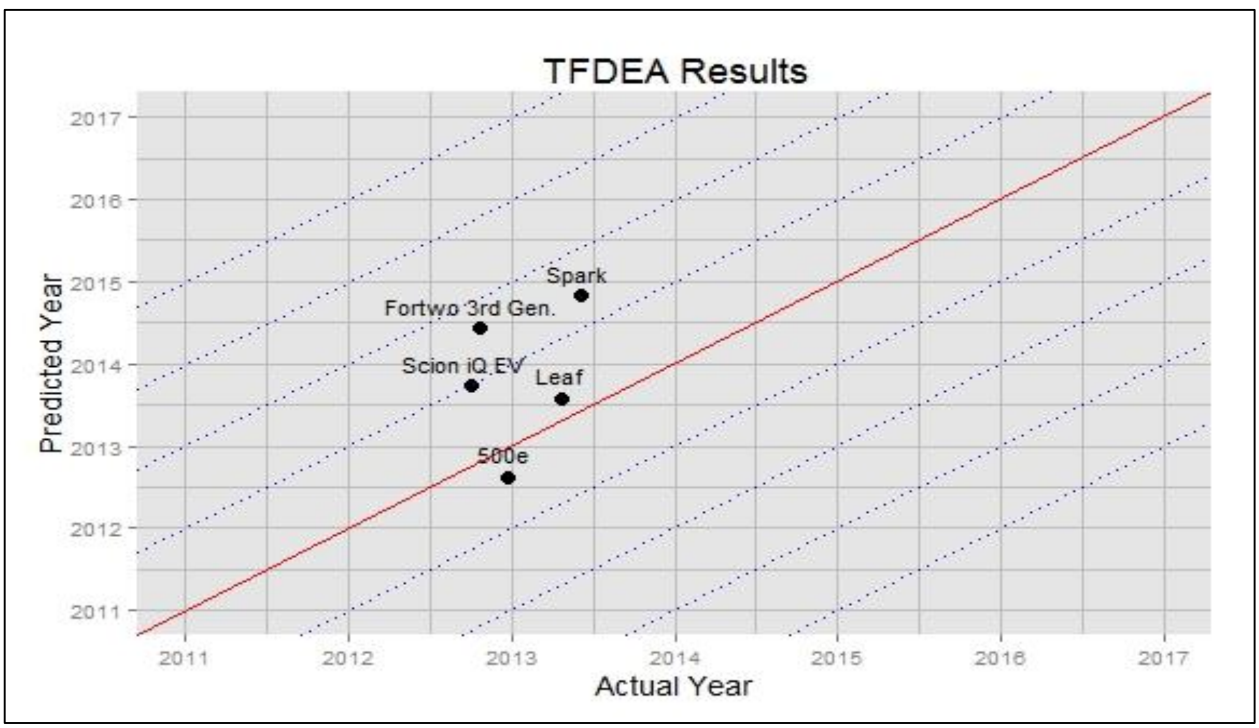


Figure 6: TFDEA Result for 2012.5 Frontier Year

Table 10 lists the forecasted results using different frontier years. The purpose of changing the frontier year and observing the resultswas to determine the impact of the first Tesla S battery released which had a energy capacity that far exceeded the other batteries. The impact of this battery can be seen by the increase in the MAD from 2012 to 2012.25, and an increase in the number of vehicles forecasted. It should also be noted that there were always vehicles that we not forecasted, which could possibly be due to the inputs and outputs selected for the TFDEA model, or because of the data collected.

Table 10: TFDEA Results with Different Frontier Years

Frontier Year	Training Data Count	Validation Data Count	MAD	Percentage Vehicles Forecast	Rate of Change (RoC)
2012	14	12	1.5366	6/12 = 50%	1.03225
2012.25	17	9	1.8120	6/9 = 66.67%	1.03101
2012.5	18	8	0.9296	5/8 = 62.5%	1.03029
2012.75	20	6	0.9685	4/6 = 66.67%	1.03072
2013	24	2	1.2618	2/2 = 100%	1.02983

6 Results Interpretation and Analysis

Due to the large investments in battery technologies and specifically EV battery technologies, a RoC of approximately 3% per year does not seem correct. However, by observing changes in the inputs and outputs of the TFDEA model over the 16 year period of available data, there does not seem to be any major improvements.To gain a better understanding on the progress of developments in the battery technologies, it would possibly be more beneficial to gather data on technology advancements from earlier R&D stages. As was determined from the data mining results, there is still major focus on the lithium-ion technology in all stages of R&D. The real advancements in this technology may still come, and therefore will not be captured in theRoC determined from the TFDEA model. Additionally, if any disruptive technology was introduced (i.e. metal-air), then again this RoC value will no longer be relevant.

Table 11 lists the 2013 frontier year forecast results for the two EV batteries released in 2013. It can be noted that the Chevy Spark forecasted just under 2 years ahead of the actual release date. This specific EV has a lower price, higher MPGe, good acceleration, and low battery weight compared to other EVs. In order to determine future characteristics of these EVs, the outputs were multiplied yearly by the average RoC, to determine the 2020 values shown in Table 12. The actual range for each EV was calculated by using the MPGe equation previously mentioned, with the current energy capacity of the EV's battery. The resulting range is far below the goal of DOE of 300 miles, which is basically due to the very low average RoC. This tells us that if current incremental advancements continue then the DOE goals cannot be met unless a new disruptive technology is introduced.

Table 11: 2013 Frontier Year EV Forecasts

Vehicle	Release Date	Efficiency at Release	Efficiency at Frontier	Forecasted Date
Nissan Leaf	2013.304	1.0000000	1.027331	2013.921
Chevy Spark	2013.419	1.0000000	1.070432	2015.326

Table 12: 2020 Forecasted Performance

Vehicle	MPGe	Acceleration	Price_2013	Actual Range*
Nissan Leaf	141.27	8.05 s	$23,444.27	99 miles
Chevy Spark	146.19	6.2 s	$22,471.91	91 miles

7 Conclusion

Data mining is a very useful tool for gaining a further understanding of the environment in which a technology exists beyond what is available only in literature. Key organizations together with the current technology emphasis for each R&D stage was easily identified from articles, patents, and newspaper abstracts. Combining these results with the TDS can help to determine whether any potential technologies may enter the market in the near or distant future, and who will be involved with these developments. Based on the data mining results in this study, focus in the basic research stage is on metal-air battery technologies. This technology could possibly replace the current lithium-ion batteries due to its high specific energy, however there may be quite a few years before it is used in EVs due to its early stage of development. By using the data mining results, it was therefore possible to identify what could possibly change the relevancy of the TFDEA forecast.

Forecasted results using the average RoCdoes not take into account the introduction of some metal-air batteries as disruptive technology.The dataset only included EVs with incremental advancements in lithium-ion batteries.An increase of approximately 3 percent per year in performance improvements does not seem to align with all the investment in place for improving the technology, however this value isvery close to a previous study on Hybrid Electric Vehicles (HEVs), where the RoC was 1.03 [28].Based on the 2020 forecast that used the average RoC, the range will be far below the goal of DOE. To possibly get a better understanding of the actual advancements in the technology, it may be beneficial to look at earlier stages of R&D.

8 Recommendations and Future Work

In order to obtain a better technology progress timeline, the DOE should do more work in terms of understanding the current situation of EV batteries. With that in mind, there is need for future work based on Gap analysis to help identify the gaps between the current situation and the future state that is desired, along with the tasks that need to be completed to close this gap. In the Future work, more emphasis should be put in future candidates technologies as there is currently a gap in technology that researchers think can be filled using Metal-air batteries. Some of these future candidates technologies primary concern is the high operating temperatures, which are the cause for safety. The DOE should invest in this problem by funding more R&D for its fast resolution. Also, future work should include more input from experts such as engineers in the EV battery field in the if possible in order to gain more valuable information in the matter. Above all, more work should be done so that any chosen technology is up to date with safety and environment requirements.

8.1 Limitations

The following is a list of limitations for this study:

- Parameters used in the TFDEA model take into account characteristics of EVs other than that of the battery. Specific energy, specific power, price, temperature, etc., for each battery would be the preferred parameters,
- Data mining for lithium-ion batteries should be broken down into the different chemistries available,
- Safety factors should be included in the forecast since it can limit the overall progress of the technology,
- Battery performance data and criteria can vary depending upon many factors, such as vehicle size, weight, body shape and the driving habit of the driver. The assumptions are not commonly published,
- Data was difficult to obtain due to the confidentially of companies regarding this information. Therefore, this study was limited to battery technologies that have already been released into the market. There are batteries that can possibly meet the DOE requirements, however it is not currently in the marker and therefore was not taken into account in the forecasts.

8.2 Future Work

The following is a list of future work that can be conducted to improve and extend this study:

- More data should be gathered that is specific for the battery only and a more specific TFDEA model should be created,
- Due to the large range of lithium-ion batteries, the data mining work should be extended to all different chemistries that are available,
- Potential disruptive technologies should be discussed with industry experts and incorporate into the forecasts,
- Alternative forecasting methods should be used and compared with the results obtained in this study.

References

[1] B. K. Sovacool and R. F. Hirsh, “Beyond batteries: An examination of the benefits and barriers to plug-in hybrid electric vehicles (PHEVs) and a vehicle-to-grid (V2G) transition,” *Energy Policy*, vol. 37, no. 3, pp. 1095–1103, Mar. 2009.

[2] M. a. Tamor, C. Gearhart, and C. Soto, “A statistical approach to estimating acceptance of electric vehicles and electrification of personal transportation,” *Transp. Res. Part C Emerg. Technol.*, vol. 26, pp. 125–134, Jan. 2013.

[3] S. G. Wirasingha, N. Schofield, and A. Emadi, “Plug-in hybrid electric vehicle developments in the US: Trends, barriers, and economic feasibility,” *2008 IEEE Veh. Power Propuls. Conf.*, pp. 1–8, Sep. 2008.

[4] M. Ramsey, “Ford CEO: Battery is Third of Electric Car Cost,” *Wall Street Journal*, 2012.

[5] K. G. Gallagher, D. Dees, and P. Nelson, “PHEV Battery Cost Assessment,” 2011.

[6] M. Catenacci, E. Verdolini, V. Bosetti, and G. Fiorese, “Going electric: Expert survey on the future of battery technologies for electric vehicles,” *Energy Policy*, vol. 61, pp. 403–413, Oct. 2013.

[7] R. Nault, “Argonne lab data.” .

[8] K. Young, C. Wang, L. Y. Wang, and K. Strunz, *Electric Vehicle Integration into Modern Power Networks*. New York, NY: Springer New York, 2013.

[9] D. Howell, T. Lead, and E. Systems, “Vehicle Technologies Program,” 2010.

[10] E. Loveday, “WSJ: Nissan Leaf profitable by year three; battery cost closer to $18,000,” *Autoblog Green*, 2010. [Online]. Available: http://green.autoblog.com/2010/05/15/nissan-leaf-profitable-by-year-three-battery-cost-closer-to-18/. [Accessed: 02-Dec-2013].

[11] V. Srinivasan, “Batteries for Vehicular Applications,” Lawrence Berkeley National Lab.

[12] Element Electricity Limited, “Cost and performance of EV batteries: Final report for The Committee of Climate Change.” 2012.

[13] A. Pesaran, “Battery Choices for Different Plug-in HEV Configurations,” 2006.

[14] K. Bullis, “Is Tesla Working on a Cheap, 300-Mile ‘Metal Air’ Battery?,” *MIT Technology Review*, 2013. .

[15] J. P. Christophersen, C. D. Ho, C. G. Motloch, D. Howell, and H. L. Hess, “Effects of Reference Performance Testing during Aging Using Commercial Lithium-Ion Cells,” *J. Electrochem. Soc.*, vol. 153, no. 7, p. A1406, 2006.

[16] A. Pesaran, C. Ban, A. Brooker, A. Dillon, J. Gonder, J. Ireland, G. Kim, K. Lee, D. Long, J. Neubauer, S. Santhanagopalan, K. Smith, R. Tenent, E. Wood, and C. Shaffer, “NREL Energy Storage Projects – FY2012 Annual Report NREL Energy Storage Projects – FY2012 Annual Report,” no. March, 2013.

[17] J. P. Christophersen, J. R. Belt, and R. B. Wright, “DOE Advanced Technology Development Program for Lithium-Ion Batteries : INEEL Gen 1 Final Report,” no. September, 2001.

[18] S. Schoenung and D. Ph, “Energy Storage Systems Cost Update A Study for the DOE Energy Storage Systems Program,” no. April, 2011.

[19] D. L. Anderson and D. Patiño-echeverri, “An evaluatin of current and future costs for lithium-ion batteries for use in electrified vehicle powertrains,” Duke University, 2009.

[20] A. Durmusoglu and T. Dereli, “On the technology forecasting using data envelopment analysis (TFDEA),” 2011, pp. 1 –6.

[21] T. R. Anderson and L. Inman, “Resolving the Issue of Multiple Optima in Technology Forecasting Using Data Envelopment Analysis 1,” in *Technology Management in the Energy Smart World (PICMET), 2011 Proceedings of PICMET ’11*, 2011, pp. 1–5.

[22] L. Inman, “TFDEA: A New Approach for Technology Forecasting of New Product Development Targets,” 2004.

[23] J. P. Martino, “A Review of Selected Recent Advances in Technological Forecasting,” *Technol. Forecast. Soc. Change*, vol. 70, no. 8, pp. 719–733, Oct. 2003.

[24] R. Earley, L. Green-weiskel, L. Kang, F. An, and L. Green-Weiskel, “Electric Vehicles in the Context of Sustainable Development in China,” New York, NY, 2011.

[25] S. Wasserman and K. Faust, *Social network analysis : methods and applications*. New York, NY: Cambridge University Press, 1994.

[26] B. Canis, “Battery Manufacturing for Hybrid and Electric Vehicles : Policy Issues.” CRS Report for Congress, 2013.

[27] A. T. Roper, S. W. Cunningham, A. L. Porter, T. W. Mason, F. A. Rossini, and J. Banks, *Forecasting and Management of Technology*, Second. Hoboken, NJ: Wiley, 2011.

[28] S. R. Jahromi, A.-A. Tudori, and T. R. Anderson, “Forecasting Hybrid Electric Vehicles using TFDEA,” in *Technology Management in the IT-Driven Services (PICMET), 2013 Proceedings of PICMET ’13*, 2013.

[29] R. Earley, L. Green-weiskel, L. Kang, F. An, and L. Green-Weiskel, “Electric Vehicles in the Context of Sustainable Development in China,” New York, NY, 2011.

A] [M1] L. Inman, T. R. Anderson, and R. Harmon, "Improving time to market forecasts: a comparison of two technology forecasting techniques for predicting U.S. fighter jet introductions from 1944 to 1982," in *A Unifying Discipline for Melting the Boundaries Technology Management:*, 2005, pp. 533–537.

C] [M3] D. Lim and T. Anderson, "An introduction to Technology Forecasting with a TFDEA Excel add-in," in *Technology Management for Emerging Technologies (PICMET), 2012 Proceedings of PICMET '12*, 2012, pp. 1293–1298.

D) [M4] Montgomery, Douglas C., Elizabeth A. Peck, and G. Geoffrey Vining. *Introduction to linear regression analysis*.Vol. 821.Wiley, 2012.

F][Miii] Martino (1993), "Technological Forecasting for Decision Making", McGrawHill.

Appendix A: Data

Product	Make	Model Year	Release Date	Battery Weight (kg)	Acceleration 0-60 MPH	MPGe	2013 Price ($)
RAV4	Toyota	1997	1/1/1997	550	18	72	61114.84
GM EV1	GM	1999	1/1/1999	481	8	37	47662.45
Hyper Mini	Nissan	1999	1/1/1999	267	30	75	51260.96
Altra	Nissan	2000	1/1/2000	365	15.5	85	69168.68
fortwo 1st gen	Mercedes	2007	1/1/2007	110	30	87	35690.97
Tesla Roadster	Tesla Motors	2008	2/1/2008	450	3.7	119	118235.8
Mini MiniE	BMW	2009	6/1/2009	259	8.5	98	54430.24
iOn	Peugeot	2010	1/1/2010	200	15.9	105	42630.48
C-Zero	Citreon	2010	1/1/2010	200	15.9	105	53872.08
Fluence Z.E.	Renault	2010	1/1/2010	250	12.5	105	37486.29
fortwo 2nd gen.	Mercedes	2011	9/17/2010	163	6.5	87	17650.48
Leaf	Nissan	2011	12/10/2010	290	10	99	36785.68
i-Miev	Mitsubishi Motors	2012	10/17/2011	246	9	112	32652.54
Active E	BMW	2011	12/2/2011	276	8.5	102	62659.21
Model S (85 kW-hr)	Tesla	2012	2/27/2012	500	5.4	89	81275.32
CODA Sedan	CODA	2012	2/27/2012	408	9.6	73	37891.18
Focus Electric	Ford	2013	3/5/2012	327	9.5	105	39200
Fit EV	Honda	2013	6/15/2012	224	8.4	118	36625
RAV4 EV Gen2	Toyota	2012	9/7/2012	455	18	76	50657.21
Scion iQ EV	Toyota	2013	9/29/2012	219	14	121	45000
fortwo 3rd gen.	Mercedes	2013	10/22/2012	178	13	107	25750
ZOE	Renault	2012	12/1/2012	290	13	90	27719.05
Model S (60 kW-hr)	Tesla	2013	12/4/2012	353	5.9	95	69900
500e	Fiat	2013	12/20/2012	261	9	116	33630
Leaf	Nissan	2013	4/22/2013	273	9.9	115	28800
Spark	Chevy	2014	6/3/2013	270	7.6	119	27500

Appendix B: Results

Table 13: 2012.5 Frontier Year Forecast

Vehicle	Release Date	Efficiency at Release	Efficiency at Frontier	Forecasted Date
RAV4 EV 2nd Gen	2012.685	0.6596	0.6596	-
Scion iQ EV	2012.745	1.0000	1.0374	2013.730
Fortwo 3rd Gen	2012.808	1.0000	1.0596	2014.439
ZOE	2012.918	0.8666	0.8724	-
Model S (60 kW-hr)	2012.926	0.8112	0.8112	-
500e	2012.970	1.0000	1.0037	2012.629
Leaf	2013.304	1.0000	1.0329	2013.586
Spark	2013.419	1.0000	1.0720	2014.829