A General Approach to Electrical Vehicle Battery Remanufacturing System Design

by

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To my family

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ABSTRACT

One of the major difficulties electrical vehicle (EV) industry facing today is the production and lifetime cost of battery packs. Studies show that using remanufactured batteries can dramatically lower the cost. The major difference between remanufacturing and traditional manufacturing is the supply and demand variabilities and uncertainties differences. The returned core for remanufacturing operations (supply side) can vary considerably in terms of the time of returns and the quality of returned products. On the other hand, because different contracts can be used to regulate suppliers, it is almost always assumed zero uncertainty and variability for traditional manufacturing systems. Similarly, customers demand traditional manufacturers to sell newly produced products in constant high quality. But, remanufacturers usually sell in aftermarket, and the quality of the products demanded can vary depends on the price range, usage, customer segment and many other factors. The key is to match supply and demand side variabilities so the overlapping between them can be maximized. Because of these differences, a new framework is needed for remanufacturing system design.

This research aims at developing a new approach to use remanufactured battery packs to fulfill EV warranties and customer aftermarket demands and to match supply and demand side variabilities. First, a market lifetime EV battery return (supply side) forecasting method is develop, and it is validated using Monte Carlo simulation. Second, a discrete event simulation method is developed to estimate EV battery lifetime cost for both customer and manufacturer/remanufacturer. Third, a new remanufacturing business model and a simulation framework are developed so both the quality and quantity aspects of supply and demand can be altered and the lifetime cost for both customer and manufacturer/remanufacturer can be minimized.

The business models and methodologies developed in this dissertation provide managerial insights to benefit both the manufacturer/remanufacturer and customers in EV industry. Many findings and methodologies can also be readily used in other remanufacturing settings. The effectiveness of the proposed models is illustrated and validated by case studies.

CHAPTER 1

Introduction

1.1 Motivation

Energy and environment are two major social concerns today, and electrical vehicles (EV) have enormous potential to positively impact their future. EVs also become increasingly trendy in recent years. General Motors (GM) invested almost half billion USD and thousands of engineers in 2014 for its next generation "electrification" (GM, 2014). Similarly, Tesla, a growing leader in semi-autonomous EVs, is fueled by US$4.9 billion of government's subsidies (Hirsch, 2015). Almost all major automotive manufacturers are investing significant amount of money and resources into the development, manufacturing, and marketing of EVs. Despite this tremendous effort, the total number of EVs sold each year is still insignificant compared to the sales of internal combustion engine (ICE) vehicles in the U.S., at around only 1% of the total market share (EVVolumes, 2016). Moreover, there are plenty of governmental incentives at the federal, state, and local levels. For example, if a resident in Sonoma county, California purchases a new EV, such as Nissan Leaf or Tesla Model S, he/she can receive $10,500 in incentive, $7,000 from federal, $2,500 from state and $1,000 from the county (DriveClean, 2016). However, these heavy incentive programs have not been effective at bringing sales up.

Among many factors contributing to this problem, high selling price is arguably the most important factor from the customers' perspective. In many cases, lowering the price can boost sales dramatically. For instance, Forbes reported that after Nissan lowered the price of its Leaf EV by US$6,000 in 2013, sales jumped 18% (Dan Bigman, 2013). The high price problem is attributable to various factors, and production cost is one of the main issues. Out of all the components in an EV, the battery pack creates the greatest burden in cost. Although the exact cost for a battery pack is confidential for most manufacturers, it is reported that a Nissan Leaf's battery pack costs as much as $18,000 to replace (Eric Loveday, 2010), and a Ford Focus EV battery pack costs $12,000 to $15,000 apiece (or one third to one half of the car's cost) (Ramsey, 2012). The battery alone can cost as much as a compact car. Within a battery pack, the most expensive components are the battery cells. Argonne National Laboratory's Center for Transportation provides a percentage breakdown for manufacturing cost of an EV battery; 80% is battery cell and material related (IJESD, 2000). It is estimated that it costs Tesla $195 per kWh and GM $215 kWh to produce their battery packs in 2016 (InsideEVs, 2016). Because of this high cost, many manufacturers sell EVs at a loss. Fiat-Chrysler stated that every time a Fiat 500e is sold, company losses $10,000 to $14,000 (P. Samaras, 2014; AutoWeek, 2011).

Moreover, battery packs usually cannot last for the entire lifespan of an EV, so a second, or subsequent battery pack, is needed to continue using the vehicle. Battery packs in current generation EVs can only last 6 to 8 years under the engineering specifications for vehicle power batteries. However, the average ownership of passenger vehicles is around 12 years. To resolve this issue, Nissan introduced a $100-per-month battery replacement program for their Leaf EV (for 2nd battery pack) in 2014. Although gasoline is not used, the sum of the initial purchase cost and the life-cycle cost for EVs is actually significantly higher than an ICE car's cost of ownership. Currently, this circumstance is not an issue because the majority of the EV batteries haven't reached its end-of-life. In addition, to attract more customers, original equipment manufacturers (OEMs) for EVs usually provide a liberal warranty, even at a loss. In many cases, the battery warranty is sufficiently long, such that, even if old battery degrades, a brand-new battery is given to customer for free (at OEM's cost) as replacement.

Furthermore, battery technology development cannot keep up with the automotive industry. Even though some manufacturers, such as Tesla, claim that battery cell's price can go to $100 per kWh by 2025 (GreenTechMedia, 2016), the battery pack for a Tesla Model S will still cost more than $22,000 to produce, if other related electronics are included. On the other hand, a brand-new low trim Honda Civic, a very popular small size sedan, only costs $16,000. Hence, OEMs are desperately trying to lower the battery cost, and they cannot entirely depend on technology improvements.

One way to solve this problem is to alter EV business models, such as remanufacturing the battery packs. The business model used in both manufacturing and auto industries has changed tremendously in the past decade. Manufacturing and other heavy machinery industries are gradually shifting to a "servitization" business strategy. Simply speaking, OEMs no longer sell products or machineries, but are selling machine usage time. All other matters, such as maintenance, training, sometimes even operation can be included as part of their service. (Oliva & Kallenberg, 2003) described the servitization journey as a sequence of phases with increasing service content as in Figure 1-1 ((Oliva & Kallenberg, 2003)). From selling products to taking responsibility of the customer's business, servitization gradually changes the ownership and relationship between OEMs and customers. Similarly, as Uber, Lyft and other car sharing companies become increasingly popular, the definition of car ownership is also changing in the auto industry.

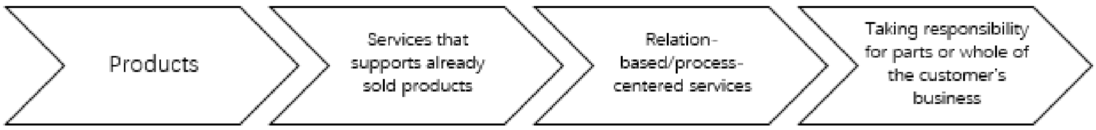


Figure 1-1. The "servitization" process (Oliva & Kallenberg, 2003)

In addition, EV OEMs, such as Tesla and many Chinese EV companies, are also expanding their charge stations. Tesla is even building battery swapping stations. This changes the interaction dynamics between EV OEMs and customers dramatically. Auto manufacturers are shifting from no interaction with customers to frequent interactions. As shown in Figure 1-2, as new business models develop, a full spectrum of ownership types and interactions are coming into existence.

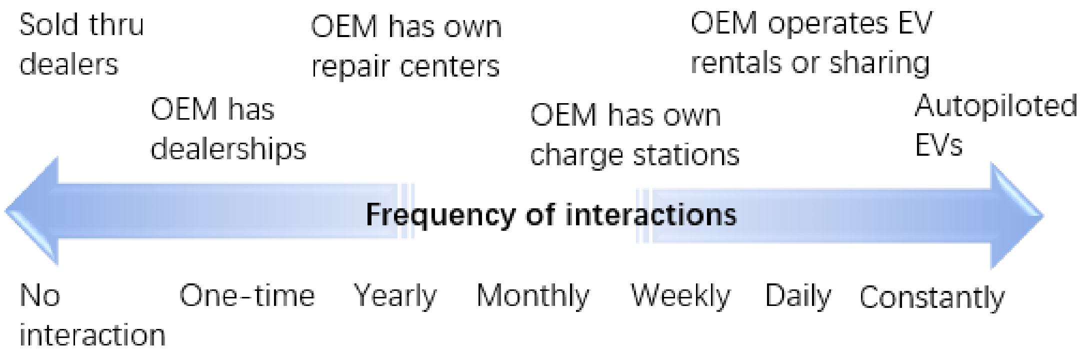


Figure 1-2. Spectrum of different types of manufacturer-customer relationships

As interactions become more frequent and ownership of the car becomes more ambiguous (sharing between customers and OEMs), it is possible to create EV power battery remanufacturing programs. In an early attempt Tesla built battery swap stations in early 2016, their business model is still largely unknown, and other business models have not matured enough for detail research. For this research, the approach for establishing a battery remanufacturing program is considered and focused on the repair-center level interactions.

It is estimated that battery remanufacturing costs 20% of the original cost to manufacture (Jin, Hu, Ni, & Xiao, 2013), and remanufactured batteries can be used as a sufficient battery replacement after the first battery retires. The intuition is very straightforward: if battery warranty is 8 years and battery fails during the 7th year, the manufacturer only needs to replace a battery that lasts for 1 year or longer. A new battery that can last 7 or 8 years is excessive. Moreover, if a battery dies during the

9^{th} year and the customer only wants to use the car for 12 years, this customer can buy a battery replacement that can last for 3 years. He/she most likely does not want to spend another $15,000 ~ $20,000 for a new battery replacement.

1.2 Remanufacturing

Remanufacturing may have different meanings in different industries. It is usually defined as "an industrial process to recover value from the used and degraded products to like-new' condition by replacing components or reprocessing used component parts" (Lund, 1984). In this dissertation, it is the process to reconstruct a product, to certain specifications, from field returned used products and/or newly manufactured components. One aspect that is different from other industries is that the final remanufactured product may be a mixture of used and new parts. That is, traditional suppliers are also part of the supply network, whereas many other remanufacturing industries, such as tire and container remanufacturings, only use returned parts as their supply.

In addition, remanufacturing and reuse of returned EV batteries are very different from the simple waste recycling and remanufacturing. It requires a systematic method to manage the used vehicle battery subsystems. The general process of diagnosis, disassembly, testing, sorting, reassembly, and testing is more complicated than most other remanufacturing processes. The importance of sustainably managing large numbers of failed EV batteries with proper end-of-life treatment has been recognized, but the fundamental research issues are still not wellunderstood and systematic methodologies and challenges to solve the problems are lacking (Jin, 2012).

Remanufacturing also provides economic incentives to firms by selling the remanufactured products and extending the life cycles of products. Successful examples from industry, such as BMW, Cummins, IBM, and Xerox, show that remanufacturing can be profitable and there is a big market for the secondary use of remanufactured products. According to the EPA, the estimated total annual sales of 73,000 remanufacturing firms in the United States were US$53 billion in 1997. The fact that remanufacturing can be profitable has also been well documented (Ayres, Ferrer, & Van Leynseele, 1997; Lund, 1983).

1.3 Research Issues

Currently, remanufacturing researches can be divided into three main fields: designing, planning and processing. Designing primarily includes product design and remanufacturing system design. System design can be further divided into remanufacturing supply chain, facility, and process design. From business perspective, designing also includes subjects such as pricing and remanufactured product marketing. Planning contains market and return forecasting, process sequencing, job sequencing, capacity planning, inventory management, uncertainty management, product acquisition and so on. Processing mainly focuses on the physical aspect of the operation, and it is comprised of disassembly, cleaning, inspecting, sorting, re-assembly and many more. However, the structure of research still follows the traditional approach used in manufacturing research.

In order to have a better understanding of the remanufacturing system, it is important to understand what the major/fundamental differences between a traditional manufacturing system and remanufacturing system are. These differences are summarized in Table 1-1 and explained below.

From a system's perspective, it is critical to determine the characteristics of its inputs and outputs. Essentially, a system is only a mechanism to transfer available inputs to desirable outputs. For traditional manufacturing systems, their input or supply side is assumed to be completely predictable and controllable through contracts with suppliers. For their demand side, or the output, only quantity and timing are somewhat predictable or controllable; all other aspects are assumed to be completely predictable and controllable. On the other hand, for a remanufacturing system, its supply side or the cores/product returns are highly unpredictable and uncontrollable in all aspects of quantity, quality and timing. Similarly, the quantity, quality and time of its demand are also full of uncertainties and fluctuations. Although remanufacturing has been studied and implemented for decades, this fundamental challenge, namely matching supply side and demand side fluctuations and uncertainties, is still largely untouched.

Table 1-1. Traditional manufacturing and remanufacturing comparisons

		Traditional manufacturing	**Remanufacturing**
Supply	Quality	Completely controllable thru	Somewhat predictable,

		contracts	uncontrollable
	Quantity	Completely controllable thru contracts	Somewhat predictable, uncontrollable
	Timing	Completely controllable thru contracts	Somewhat predictable, uncontrollable
Demand	Quality	Completely controllable by manufacturer	Maybe predictable and controllable
	Quantity	Somewhat predictable, uncontrollable	Somewhat predictable, uncontrollable
	Timing	Somewhat predictable, uncontrollable	Somewhat predictable, uncontrollable

Currently, this is solved by creating "buffers" within the system. In traditional manufacturing systems, buffering can be achieved by individual or some combinations of inventory, capacity and time. Using production line as an example, assume the main uncertainty or fluctuation is caused by machine failures. Inventory buffers means there are stocked spare parts between machines, so if a machine is down, both upstream and downstream machines can use this buffer as a cushion and continue to produce without stoppage. Time means prolonging the cycle time or the task time. If a part can be finished in 30 seconds, but the cycle time is set to 45 seconds, the extra 15 seconds can be used as a cushion for sudden events, such as machine failures. Alternatively, capacity can be increased. If a machine is often down, a similar or backup machine can be placed in parallel to increase its capacity. However, all three methods have similar down side, namely, reduced efficiency or productivity. Increasing inventory will increase work-in-progress (WIP).

Increasing time will decrease efficiency. Increasing capacity will decrease utility.

Similarly, remanufacturing systems also implement “passive buffers”. In addition, it also uses price as a buffer, such as the high profit margin in medical devices, aerospace, electricity generators or large machineries. Because profit margin is high, it is still profitable after 40 to 50% fluctuations. Therefore, in the context of remanufacturing, high profit margin and small input/output fluctuation industries can thrive. This observation is one of the main reasons remanufacturing flourishes in only a handful of industries; both demand and supply are highly predictable or “buffers” can easily be placed.

The purpose of this dissertation research is to explore alternative possibilities besides creating “passive buffers”. It is well known in other engineering disciplines, such as electrical, control and system engineering, that a better way to cope with uncertainties and fluctuations from both the input and output is to create a feedback loop. In this scenario, the traditional remanufacturing system needs to be expanded. Therefore other elements, such as customers and the manufacturing system, need to be included into the system under study.

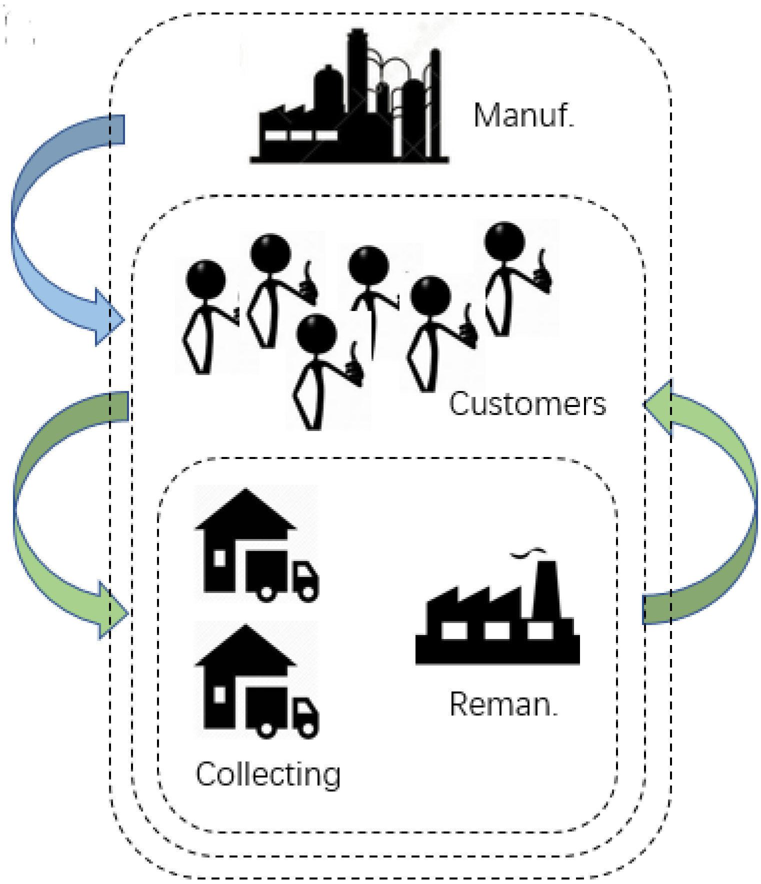


Figure 1-3. Possible remanufacturing systems when different parties are included.

To create a closed loop as shown in Figure 1-3, customers need to be linked with the remanufacturing system. The best way to link them is through business contracts between remanufacturers and other manufactures. This is where the "servitization" concept comes in. Although this is not yet widely implemented in remanufacturing industry, it exists in small scale. For example, some printer OEMs sign contracts with their large customers and guarantee the cartridge and toner usage for certain period. During this time period, the return and supply of cartridges and toner replacements can be regulated by the printer OEMs. Essentially, it creates a “closed loop” between OEMs and customers.

The key of this research is to reduce both demand side and supply side fluctuations and uncertainty by creating a similar “closed loop” between EV OEMs and customers. To establish this loop, the traditional one-time contractual relationship (car purchasing) needs to be extended to a lifelong relationship. Luckily, modern EV OEMs, such as Tesla, also operate their own repair centers and charge stations (gas station equivalent), and car warranties can be implemented, similar to those used for printer cartridge/toner contracts. By implementing more effective warranty and repair/remanufacturing policies, OEMs can better forecast customers’ behavior and have a more predictable and controllable remanufacturing system.

On the other hand, remanufacturing faces uncertainties and fluctuations in both supply and demand sides. Unlike traditional manufacturing, quality can also be different. Remanufacturing supply side is mainly dependent on returned core, or a used product returned by customers. After certain period of usage, the product can be worn and torn differently depending on customers, so all three attributes (timing, quality and quantity) of the return are almost impossible to regulate compared to traditional manufacturing. For the demand side, as illustrated by Chapter 4 of this research, customers also demand different quality of products at different times. The quality can be dependent on many factors, such as warranty period, usage, expected product life-time, expected using time and many more.

Besides coping with uncertainty and fluctuations, there are other research issues, such as battery degradation. Over the life of the battery, the battery may be charged and discharged for hundreds or even thousands of cycles. As this occurs, the individual energy storage cells may age differently. Cells may degrade at different rates. If this phenomenon is not corrected, one or more cells may become undercharged or overcharged, either of which can lead to accelerated degradation or failure of the battery packs.

1.4 Research Objectives

To achieve the goal of matching supply side and demand side variability, this study is divided into three stages. In first stage, a mathematical formulation is derived and used to predict both the quality and quantity of return during the entire market lifespan of the EV battery packs. In this stage, objectives can further be divided into:

- Determination of factors that affect returns
- Integration of factors into a coherent formulation
- Representation of the demand as a three-dimensional curve
- Validation of the above formulation with simulation and numerical examples

Matching the variables cannot be implemented in abstract, and it needs to be considered in a business setting. For the remanufacturing of EV battery packs, warranty fulfillment becomes the nature linkage between customers and OEMs. Here, it is assumed the OEM is also the remanufacturer. For supply side, because of warranty, OEM can obtain used battery packs from customers as packs are broken down. For the demand side, in some situations, remanufactured packs can be used as battery replacement to fulfill warranties. To simplify both the quality and quantity dimensions of both supply side and demand side matching process, cost is used. That is, parts with different qualities are translated to monetary values and are matched by monetary terms. Thus, stage two is to determine different costs for both customers and OEMs during both the individual lifespan of an EV car and the entire market lifespan. In this stage, objectives are divided into the following tasks:

- In addition to factors from stage one, determine how different factors affect costs (e.g. warranty terms, repair types, and degradations).
- Integrate all the factors using discrete event simulation (DES).
- Determine the lifetime costs for customer and the OEM.
- Determine the total market lifespan cost for the OEM
- Determine the total market lifespan cost and cost schedule for the OEM

In stage three, everything from stages one and two are included. The matching process essentially is to shift both the 3D demand and supply curves and to change the shapes of these curves to maximize the overlapping area between them. The objectives are divided into the following tasks:

- In addition to the influential factors in stages one and two, determine replacing/repairing schemes and inventory factors affecting return
- Generate 3D demand and supply curves
- Determine how different matching strategies can shift and change the shapes of these curves
- Maximize the overlap between supply and demand curves

1.5 Outline of the Dissertation

The rest of the dissertation is divided according to the three stages listed above. In Chapter 2, only the supply of the remanufacturer is considered. Customers are linked with OEMs through the warranty contract, and the main focus is to predict the timing, quality and quantity of supply side or the battery return. For this study, the EV sales distribution, battery breakdown distribution and customer return distribution are studied. In Chapter 3, different costs are determined. Again, OEMs are linked with customers through the warranty contract. The four types of costs for the warranty are illustrated. Beside the influential factors listed in Chapter 2, warranty, usage rate and battery degradation are also studied. In Chapter 4, both supply and demand sides are considered. All three parties: manufacturer, customer and remanufacturer are included in the system. The focus is to match both input and output uncertainties and fluctuations. For this study, manufacturer and remanufacturer are considered to be one entity or the same firm, so all information between them is transparent and all actions are synchronized. All influential factors from both Chapters 2 and 3 are included. In addition, different repair/remanufacturing schemes and inventory policies are also studied. Conclusion is given in Chapter 5.

CHAPTER 2

Forecasting Product Returns for Remanufacturing Systems

2.1 Background

As the global manufacturing environment becomes increasingly competitive, more and more manufacturers view remanufacturing as an important opportunity for profit generation. Remanufacturing provides a means for a society to treat product life cycle from a more holistic perspective, offers an alternative to traditional recycle and reuse, and increases resources utilization. Remanufacturing is the process that recovers residual value from used or degraded products by disassembly and recovery at module level or at component level. This is accomplished by restoring used products to 'like-new' condition by replacing broken or degraded components or by reprocessing used components (Sutherland, Adler, Haapala, & Kumar, 2008; Lund, 1984). Focusing on value-added recovery is the main difference between remanufacturing and other types of end-of-life (EOL) treatments, such as recycling (Westkämper, Alting, & Arndt, 2001; Guide, 2000). This is also the reason that remanufacturing systems are viewed and treated more similar to traditional manufacturing systems than simple recycling.

Remanufacturing is a fast-growing industry. In the United States alone, remanufacturing operations (excluding military) has a $53 billion per year market share (Hauser & Lund, 2003), and it is growing from between 10% to above 50%, depending on industry and product types (Sahay, Srivastava, & Srivastava, 2006). Automotive Parts Remanufacturers Association estimated that the remanufactured units were roughly 10 million in 1995, 15 million in 2000, 20 million in 2005, and 30 million in 2015 (Buxcey, 2003).

The variability of both supply and demand sides are the most critical issues facing industry today. Many other remanufacturing topics, such as inventory management, are designed to either isolate or mitigate these fluctuations. In a survey (Hammond, Amezquita, & Bras, 1998), 43% of automotive part remanufacturers considered that parts availability was the number one difficulty for their operation, and 41.2% of them used the availability of parts as the main criterion to decide whether or not to remanufacture a given product. A number of research groups (Marx-Gomez, Rautenstrauch, Nürnberger, & Kruse, 2002; Guide, Jayaraman, & Srivastava, 1999) stated that the uncertainty in time and amount was the single most important factor that influenced remanufacturing system planning. Guide et al. (2000) listed seven major problems that remanufacturing systems faced today, and three of them were related to this problem. Uncertainty from supply side (returned products) is the most crucial characteristic of remanufacturing problems, and it distinguishes remanufacturing from traditional manufacturing systems. Unlike traditional manufacturers, remanufacturers usually have less or no direct control of the returned parts. Figure 2-1 illustrates an example of variations in both supply and demand sides. From a remanufacturer's perspective, supply is the volume of returned used products, and demand is how many remanufactured products are desired. The overlapping area denotes remanufacturable quantity when delays in inventory, remanufacturing time, and other factors are neglected. As the figure shows, remanufacturing operations are essentially matching processes that intend to maximize the overlapping region under demand and supply curves, and in order to match, forecasts of both supply and demand curves are necessary. Moreover, in addition to the variations in quantity and arrival times, quality variation is equally important since returned products can have a wide range of conditions, but finished products usually need to meet the same quality specification. This poses a unique problem that traditional manufacturing systems do not encounter, so new techniques are needed to predict and actively change the shape of both supply and demand curves. Preceding research have considered incentives, such as discount and advertisements, into account to optimize the overall remanufacturable volume (Ghoreishi, Jakiela, & Nekouzadeh, 2011). This study is more focused on the prediction of the supply curve.

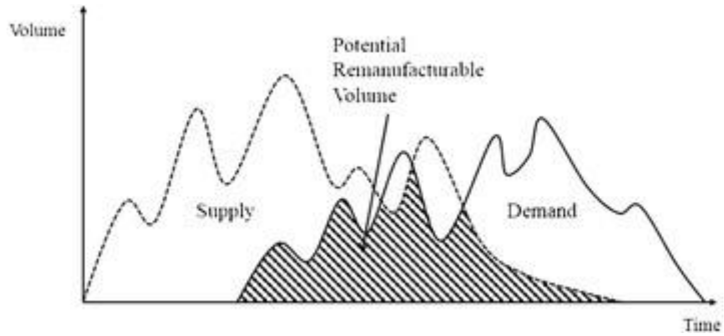


Figure 2-1. Remanufacturable products are the area supply and demand (for illustration only)

There exists a spectrum of remanufacturing scenarios, which have very different types of return characteristics. For example, the return process of leased printer is very predictable since the return date and/or quality are predefined by the leasing contracts. However, the return characteristics of many fashionable goods and consumer electronics are more random since the sales of the items, usage pattern, and customer return behavior are all unpredictable. Because of this variation in predictability, different forecasting approaches are required for different business settings. This research targets the recently developed electrical vehicle (EV) battery return applications. The urgency and importance of EV battery remanufacturing is because of limited and costly resources, the modular nature of lithium batteries, and potential resale market. Current lithium ion (Li-ion) battery-powered vehicles, such as Chevy Volt and Nissan Leaf, whose batteries are warranted for 8–10 years or 100,000–150,000 miles, are likely to fail before the expected life of the vehicles. The returned battery may still have significant residual value. The cost of Li-ion battery is still very high, usually around US$200 per kWh. Therefore, remanufacturing has great potential to dramatically reduce the total life-cycle costs of Li-ion batteries (Jin et al., 2013; Jin, Ni, & Koren, 2011). Industries also propose different types of purchase/warranty schemes in order to allow customers to have operational batteries for the entire vehicle lifespan. That is, customers are now able to purchase not only a single battery pack with the EV but also the warranty of battery use-time, or the combination of them. In this type of business scenario, broken or degraded batteries can be returned or traded in to dealers or battery collectors and be replaced with a new battery before the predefined total use-time expires. The new batteries can then be made with components from returned batteries. This creates strong incentives for customers to return the battery and for manufacturers to remanufacture. Since this business scenario is completely new, the goal of this research is to develop a long-term forecasting method to remanufacturers and related suppliers to assist their operational decisions.

The challenges for forecasting of product returns are mainly from two sources: lack of quality/credible data and unproven assumptions. There is no or very limited historical data since this type of remanufacturing business scenario has never been seen in the industry, and data is also limited or of low accuracy/credibility in similar fields. These challenges seriously limit the type of forecasting techniques that can be implemented. With these constraints, a physical model-based forecasting method, instead of traditional data-driven methods that heavily rely on data quality and sophisticated statistical models, is proposed here.

The objective of this research is to provide a methodology to forecast both quantity and quality of returned products, such as EV batteries, based on previous/expert knowledge on indirect information rather than direct historical data. The rest of this chapter is organized as follows. Literature review highlights previous literature regarding remanufacturing return forecasting. The final section summarizes this research work and points out possible future research directions.

2.2 Literature Review

Although sales forecasting has been studied for many decades, there are few scientific papers regarding return item forecasting for remanufacturers, and the majority of them are focused on short-term tactical and operation level mainly for inventory management and production planning (Guide & Wassenhove, 2003). For some scenarios, simple classical forecasting techniques, such as moving average and exponential smoothing, are sufficient (Nahmias & Cheng, 1993). However, often, there is more valuable information that people can take advantage of, and a variety of forecast outputs are required for different situations (Toktay, van der Laan, & de Brito, 2004). Therefore, specific techniques are developed to tailor to those specific needs. In some cases, periodical information, such as monthly volume, is available and the need is to predict the future volume (Clottey, Benton, & Srivastava, 2012). In other cases, historical return dates are available and other characteristics, such as return lead times, are predicted. Kelle and Silver (Kelle & Silver, 1989) developed four different forecasting methods for expected value and variance of return lead times of containers. Goh and Varaprasad (Goh & Varaprasad, 1986) used a transfer function model that included factors, such as previous returns, sales, and time lag, to predict the timing and quantity of returns of Coca-Cola bottles. Toktay et al. (Toktay, Wein, & Zenios, 2000) developed a Bayesian estimation-based distributed lag model, which used newly collected data to update estimated parameters. As listed above, the majority of existing studies use a statistics-based method for prediction with historical data.

Other types of forecasting methods that include previous knowledge, simulation, or known sub-models are often used. Marx-Gomez et al. (2002) combined simulation and fuzzy logic models to forecast the quantities and timing of returns of photocopiers. Simulation was used to obtain sales, failures, usage intensity, return quotas, and other so-called impact factors. Then, fuzzy controller was used to combine these impact factors and give one-period prognosis and neuro-fuzzy network was used to provide multi-period prognosis. Similarly, Hanafi et al. (Hanafi, Kara, & Kaebernick, 2007) used fuzzy-colored petri nets to combine different sub-models, such as technology development, consumer demands, and product reliability to forecast returns at different locations over a specific time period. For others, non-parametric models are more suitable. For example, Monte Carlo simulation can be employed to estimate the sale of products, such as CRT televisions. The gap between existing literature and our current need is that the above methods are used for prognosis and for relatively short-term prediction but not for lifespan planning of the business or facility. Furthermore, the existing literature has not addressed much on the quality variation of returned products, which is critical for battery remanufacturing. To fill the gap in the existing literature, this research develops a new forecasting tool for end-of-life product returns in terms of timing, quantity, and quality to support the remanufacturing strategic planning and decision making.

2.3 Forecasting of product return quantity

Quantity forecasts provide information on how many product returns a remanufacturer can expect in the future. However, unlike most forecasts that only deal with a one-time customer decision, such as buying or not buying, returning is determined by a series of cascaded events, i.e., product purchase decision, product usage, and product return decision. In this section, a new method is presented for predicting product returns. The key is to effectively characterize three main influencing factors—sales, life expectancy, and return behavior—to facilitate an accurate forecasting of return timing, quantity, and quality. More specifically, the reasons of product return considered in this research are limited to the failure-induced return and end-of-life return. Other factors, such as the product technology upgrading, may be reasons for why a customer returns a product, but are not considered in this work.

2.3.1 **Influence Factors**

The three influential factors are date sold, usage, and return behavior, which are related to OEM, the product, and customer respectively.

2.3.2 **Sales Distribution, S(t)**

Sales forecasting has been studied for many decades, and many manufacturers, or third-party consultants, usually have their own forecasting models. Moreover, it is common in industry that a non-analytical form of modeling is used. This is because people tend to focus more on market research perspective of the forecast. Techniques, such as concept test, focus groups, perceptual mapping, conjoint analysis, and consumer clinics, are more often seen, in order to have a better understanding of the customers' preference and to adjust future plans. For example, the information acceleration (IA) methods are used for GM's electric vehicle sales prediction (Urban, Weinberg, & Hauser, 1996). On the other hand, academic researchers are more interested in mathematics-orientated approaches because they can provide a more direct relationship among different influential factors. For this reason, this research provides both analytical and numerical methods in order to accommodate current industry practice.

For analytical-based forecasts, there are generally two categories: aggregated and disaggregated models. For aggregated or top-down approaches, only the cumulated behavior of a group of people is studied. On the other hand, disaggregated or bottom-up models study individual decision makers that underlie market demand or supply and integrate them. Although the emphasis in forecasting and econometrics has generally shifted from aggregated to disaggregated models in the past decades, most forecasting models people use in industry today are still of aggregated form simply due to the difficulty and expense of collecting data on individual consumers. Out of all aggregated models, Bass diffusion model is the most often used (Mahajan, Muller, & Bass, 1995).

Diffusion of products or innovation is the theory that seeks to explain how, why, and at what rate a new idea spreads through societies. The parameter that characterizes this process is called the rate of adoption, and it is defined as the relative speed in which members of a social system adopt an innovation. This rate is usually measured by the length of time required for a certain percentage of the members to adopt. Customers can be divided into many categories, such as innovators, early adopters, early majority, late majority, and laggards. Groups are different in how they perceive different innovation factors, such as relative advantage, compatibility, and complexity of the product. Bass diffusion model is chosen because it has all the essentials of diffusion models and yet is the most simplified and intuitive version. In this model, only two customer groups, early adopters and followers, are considered. The sales only include the originally manufactured products and the remanufactured products are only used for warranty repair but not for original sale.

Mathematically, we use the following differential equation to represent the Bass diffusion

$$\frac{f(t)}{1-F(t)} = p + qF(t), \qquad (2\text{-}1)$$

where $F(t)$ is the base function, and $f(t)$ is the rate of change or derivative of $F(t)$. p is the coefficient of early adopters, advertising effect, or innovators in Bass's original model. It describes how quickly early adaptors are willing to purchase or to enter a new market. q is the coefficient of followers, internal influence, word-of-mouth effect, or imitator factors in the original model. Sales volume at time t, $S(t)$, is the rate of change of installed base $f(t)$ multiplied by the market potential, m, and has the form of

$$S(t) = mf(t). \qquad (2\text{-}2)$$

The solution to Equation (2-1) is

$$S(t) = m\frac{(p+q)^2}{p}\frac{\exp(-((p+q)t))}{(1+{}^{q}\!/\!{}_{p}\exp(-((p+q)t)))^2}. \qquad (2\text{-}3)$$

where the time of peak sales t^* is:

$$t^* = \frac{\ln q - \ln p}{p+q}$$

In practice, p and q are set equal since early adopters usually act much quicker than followers. The choice of p and q depends on many other social factors and industry (Lilien & Rangaswamy, 2004).

2.3.3 **Product Breakdown Distribution, B(t)**

Battery life expectancy is the degree of quality degradation during the usage stage. Currently, battery condition monitoring typically refers to the evaluation of battery state of charge (SOC), or the state of health (SOH). SOC is defined as the amount of remaining charge in a battery before a recharge is required, and SOH is the potential chargeable capacity of a battery compared to the original unused one. For EV batteries, customers return a battery pack when certain degradation criteria are reached, such as when SOC drops below 75% ~85%. Therefore, the return time prediction is usually to predict the duration that a battery can last until the manufacturer's predefined threshold is reached.

The conventional approach for life expectancy prediction is to model product condition or degradation by an appropriately chosen random process, and the occurrence of failure or reaching of certain threshold is usually modeled as a Poisson process. Weibull distribution is chosen for this study because its failure rate function is only current state dependent. The system condition, or degradation state, is modeled by a Brownian motion with positive drift. Under this assumption, the time to failure corresponds to the first passage time of the Brownian motion and follows an inverse Gaussian distribution. Weibull distribution is well studied for reliability engineering, and reference can be found in many textbooks, i.e., (Rinne, 2008).

Weibull distribution is one of the solutions that assume the degradation process is deterministic. The probability density function $g(t)$, the hazard function $h(t)$, and cumulative distribution function $G(t)$ of Weibull distribution are:

$$
\begin{aligned}
g(t \mid a,b,c) &= B(t) = \frac{c}{b}\left(\frac{t-a}{b}\right)^{c-1} \exp\left(-\left(\frac{t-a}{b}\right)^{c}\right) \\
h(t \mid a,b,c) &= \frac{c}{b}\left(\frac{t-a}{b}\right)^{c-1} \qquad\qquad . \qquad (2\text{-}4) \\
G(t \mid a,b,c) &= 1-\exp\left(-\left(\frac{t-a}{b}\right)^{c}\right) \\
&\text{where } t \geq a, a \in ¡\,; b,c \in ¡^{+}
\end{aligned}
$$

Here, the breakdown function *B(t)* is exactly the probability density function, i.e., *B(t) = g(t)* (Lilien & Rangaswamy, 2004). By changing the shape parameter, the failure rate *h(t)* can be changed directly. It can be increasing, constant, or decreasing over time. Piecewise curve fitting is commonly used to model the classic bell curve for failure rate (Sharif & Islam, 1980; Pinder, Wiener, & Smith, 1978).

2.3.4 **Customer Return Function, C(t)**

The warning indicator of a battery failure is usually signaled on the dashboard of an EV, very similar to maintenance reminder signals. Additionally, similar to the maintenance behavior, people usually do not bring back the vehicle for battery treatments immediately upon observing the warning signal. This is probably due to the fact that the vehicle is still perfectly drivable and usually no noticeable changes are detected. Another reason is that SOC or SOH aspects of the battery usually degrade very gradually over a period of years without noticeable abrupt changes.

People usually do not return immediately, and sometimes the time delay between product failure and the return action can be as long as a year. The return function is usually heavily skewed to the left as illustrated in Figure 2-2. This long-tailed distribution indicates that the majority of people will return damaged or unwanted product in a short period of time. However, there are also a considerable amount of people who will return after a relatively long period of time. This kind of characteristics can be modeled by inverse Gaussian functions due to its skewness, positive support, and relatively easy expression (see Figure 2-2). Choosing inverse Gaussian is also because its flexibility in modeling the following three characteristics: (1) the majority of people return within certain time period, (2) only a small portion of them return whenever they found convenient, and (3) the rest will never return.

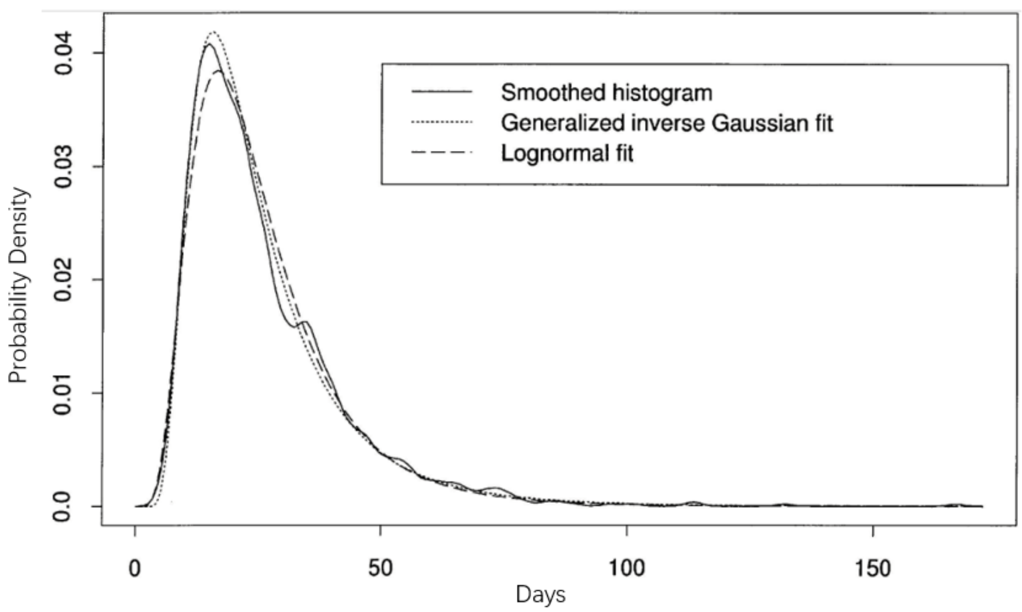


Figure 2-2. Customer return behavior distribution.

Inverse Gaussian functions have the general probability distribution function of

$$C(t) = \left(\frac{i}{2\pi t^3}\right)^{1/2} \exp\left(\frac{-i(t-j)^2}{2j^2 t}\right); i, j > 0, \qquad (2\text{-}5)$$

where $j > 0$ is the mean and $i > 0$ is the shape parameter. $C(t)$ represents the probability that the customer returns the battery t time units after its failure.

Although there are many other factors that may influence the quantity and quality of the returned products, such as government regulations, they are either not appropriate for the EV battery return in North America or not proven to have significant influence on return quantity or quality. Therefore, the three main factors listed above are the focus in this study.

2.3.5 **Return Quantity Forecasting in Continuous Case**

As illustrated in Figure 2-3, the return quantity at any point in time, such as at point *R*, is the summation of different sale quantity and product life expectancy combination. That is, returned product at *R* may be purchased at time S_1 and used for B_1 years, or purchased at time S_2 and used for B_2 years, and so on.

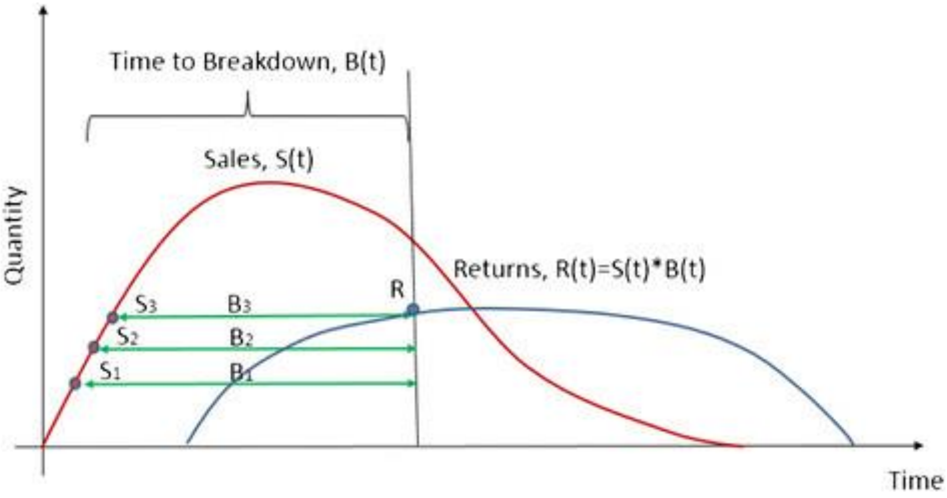


Figure 2-3. Relationship between sales, breakdown and return.

One way to characterize the relationship of these three influential factors is to use convolution. Convolution for two continuous functions *f(t)* and *g(t)* is defined as

$$f(t) * g(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau = \int_{-\infty}^{\infty} f(t-\tau)g(\tau)d\tau \qquad (2\text{-}6)$$

$$f, g : [0, \infty) \in ¡$$

For this problem, the volume of broken products at time *t* can be represented as the convolution of the sales volume *S(t)* and the breakdown probability *B(t)*. Then, the total volume of product returns at time *t*, *R(t)* is the convolution of the consumer return behavior *C(t)* and the previous convolution result *S(t)*B(t)* as follows:

$$R(t) = S(t) * B(t) * C(t) \qquad (2\text{-}7)$$

where *R(t)* denotes the return quantity at time t, *S(t)* is the probability function of sales quantity, *B(t)* is the probability function of breakdown time, and *C(t)* is the probability function of customer return. Note that *B(t)* and *C(t)* may not be normalized to unity. The integration of *B(t)* is less than unity because not all batteries are degraded to certain threshold during the lifespan of an electric vehicle. The integration of *C(t)* is less than unity because not all failed batteries are returned. Some customers may choose not to return or return to third party collectors.

However, due to the complexity of the functions *S(t)*, *B(t)*, and *C(t)*, there is no closed-form solution for the convolution. Because only a finite range is needed, these functions can be approximated over this desired range by some polynomial functions. The coefficients of the polynomial are chosen such that the weighted error between the approximation and original function is minimized in a least squares sense. For example,

$$\begin{aligned} S(t) &= \theta_0 + \theta_1 t + \theta_2 t^2 + \theta_3 t^3 + \ldots \\ \text{where } \theta_i &= \arg\min \int_a^b (R(t) - \hat{R}(t, \theta_i))^2 dt \end{aligned} \quad (2\text{-}8)$$

2.3.6 **Return Quantity Forecasting in Discrete Form**

As mentioned, most forecasting models used in industry are not analytical-based, but are most likely produced and derived from different forms of marketing research. Periodical, such as monthly or yearly, data instead of equation form of *S(t)*, *B(t)*, and *C(t)* are provided. The advantage of using a discrete form is that the raw data from reliability tests can be used directly without fitting into a model first. Similar to continuous convolution, a discrete form of convolution can be defined as

$$f[n] * g[n] = \frac{1}{l}\sum_{m=-\infty}^{\infty} f[n]g[n-m] = \frac{1}{l}\sum_{m=-\infty}^{\infty} f[n-m]g[n], \tag{2-9}$$

where both *f[n]* and *g[n]* have finite positive support, and *l* is a scale factor that is related to number of samples for both *f[n]* and *g[n]* and is used for normalization. Due to the simplicity of discrete convolution computation, many continuous functions are first discretized then are taken convolution in discrete domain. Thus, no symbolic integral of continuous functions is needed.

2.3.7 **Numerical Examples**

This section uses a numerical example to demonstrate the modeling procedure. The sales volume of battery packs is the same as the sales volume of the electric vehicles. A typical EV model usually has a market life of three to four years. Hence, it is reasonable to assume 95% of the Bass diffusion function to be in the range of [0, 4]. Substituting p =0.08, q =2, and m =1 into Equation (2-3), we obtain *S(t)* and its polynomial approximation *S˜(t)* as follows:

$$\begin{aligned} S(t) &= 54.08\frac{e^{-2.08t}}{(1+25e^{-2.08t})^2} \\ \tilde{S}(t) &= 0.011t^5 - 0.101t^4 + 0.511t^3 - 1.373t^2 + 1.631t - 0.3952 \end{aligned} \tag{2-10}$$

Note that all the approximations in this section are over interval [0, 10] or ten years. Ten-year is chosen so that it is well beyond average auto sales time of 6 to 8 years.

For breakdown function *B(t)*, it is assumed that batteries are in the "wear-out zone" in around three to four years. Failures most likely occur around the sixth year of its usage. Therefore, we have the following *B(t)* in the form of Weibull distribution:

$$B(t) = 2\left(\frac{t-3.5}{2}\right)^{3} e^{-(t/2)^{4}} \qquad \text{(2-11)}$$

$$\tilde{B}(t) = 0.005t^{6} - 0.046t^{5} + 0.249t^{4} + 1.007t^{2} - 0.588t + 0.089$$

For return behavior, assuming $\mu = 0.5$ and $\lambda = 0.2$, we have the following return function

$$C(t) = \left(\frac{0.2}{2\pi t^{2}}\right)^{1/2} e^{\frac{-0.2(t-0.5)^{2}}{2*0.5^{2}t}} \qquad \text{(2-12)}$$

$$\tilde{C}(t) = -0.017t^{6} + 0.151t^{5} - 0.749t^{3} - 2.233t^{2} + 0.117t + 1.409$$

Substituting into Equation (2-7), the resulting polynomial approximation of the return function *R(t)* is obtained:

$$\tilde{R}(t) = 0.001t^{6} - 0.074t^{5} + 0.045t^{3} - 118t^{2} + 0.086t - 0.0084. \qquad \text{(2-13)}$$

The result is shown in Figure 2-4.

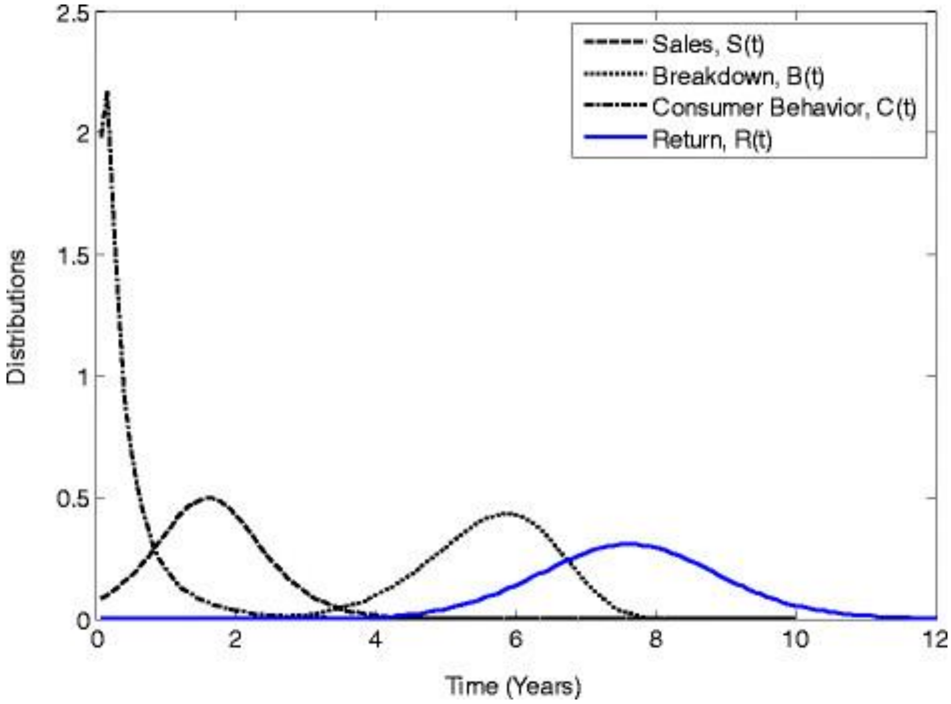


Figure 2-4. Return quantity forecasts.

2.3.8 **Monte Carlo Simulation Verification**

Another way to predict the quantity of returned products is using a Monte Carlo simulation. Monte Carlo simulation is a family of computational algorithms that rely on repeated random sampling in order to obtain the final results. Assume that the total number of customers be 100,000, thus 100,000 samples will be used. For each sample, its sale date, expected product life, and customer returns are generated according to the functions *S(t)*, *B(t)*, and *C(t)*, respectively. For sales date, it follows the Bass diffusion model as in previous sections. Technically speaking, it is not strictly a probability distribution since the integration of the function may not add to unity. Therefore, normalization is needed before sampling. For each sample, the deterministic calculation is then calculated:

$$Return\_date = sale\_date + product\_life + return\_delay$$

For aggregation, a histogram is used to obtain the distribution of sale date, product life, return delay, and return date, as illustrated in Figure 2-5.

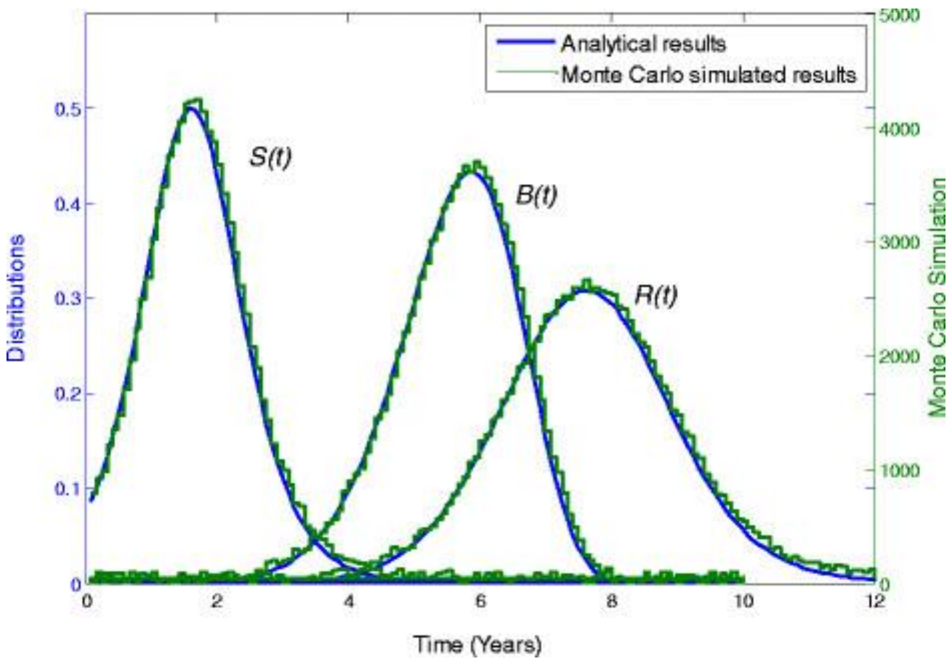


Figure 2-5. Analytical results (smooth curved) vs. Monte Carlo Simulation results (step curves).

To compare the results from Monte Carlo simulation with analytical results, the difference between two curves is measured by an f-divergence method. One of the f-divergence methods, KL-divergence value, is 0.028, and Hellinger distance is 0.035, which are all much less than unity. These calculations indicate the results obtained by both methods are very close to each other.

2.3.9 **Properties of Predicted Return Function**

Because of convolution and the general shapes of S(t), B(t), and C(t), the operation acts like a weighted moving average. This moving average can also be viewed as a “low-pass” finite impulse response filter. This means that only low frequency information will be preserved, and high frequency information will be eliminated by convolution. Here, the frequency of a function roughly means how many times a function varies in a given time interval. By taking Laplace transform in the continuous case or Z-transform in the discrete case, it can be shown that distributions used by *S(t)*, *B(t)*, and *C(t)* are essentially low-pass filters (S. W. Smith, 1997). As a result, *R(t)* is smoothed by each distribution, and any small noises found in *S(t)*, *B(t)*, or *C(t)* will be reduced. Figure 2-6 demonstrates a case where seasonality noise (a sine function), or high frequency function, is added to the sales function, *S(t)*. Sine function is chosen because it contains only a single frequency.

$$S_{noisy}(t) = (1 + 0.3\sin(8t))S(t), \tag{2-14}$$

where t is in radians. Please note that the sine function has much higher frequency than the original function. Also note that after the sine function is added, the mean, variance and the area under the curve of *S(t)* is preserved. The resulting function *R(t)* is the same before and after adding this seasonality noise component (see Figure 2-6). Due to this smoothing effect, *R(t)* is not sensitive to high-frequency changes in *S(t)*, *B(t)*, or *C(t)*.

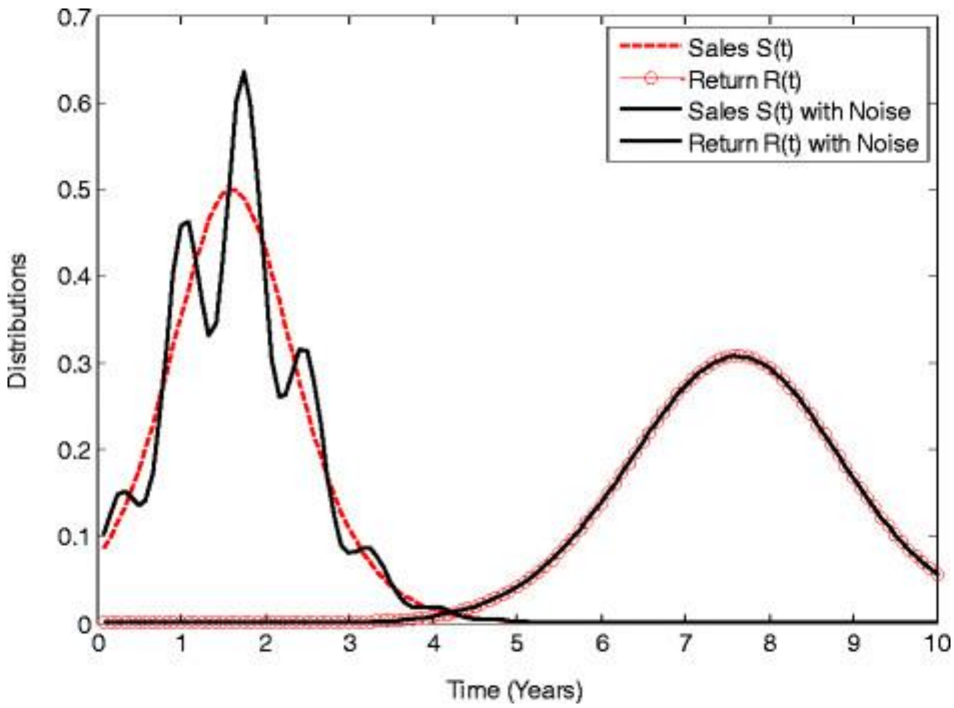


Figure 2-6. Adding high frequency noise to S(t) results in overlapping R(t)'s.

2.4 Quality Forecasting of Returned Products

Besides the quantity of the returned products, their quality is another critical factor that production planners would like to know prior to remanufacturing planning. In this study, the return product quality is defined as the remaining useful life (RUL) of the unbroken parts of a returned product. A typical EV battery pack usually consists of hundreds of battery cells. When the performance measurement of a battery pack, such as SOC or capacity, drops below certain threshold, only one or a few cells fail or degrade to unacceptable condition while the majority of the cells is still in good or reasonable quality. Because not all the cells degrade at the same rate, it is critical to estimate the RUL of good cells, so the remaining value can be assessed. RUL is essentially a conditional probability distribution that determines how long it takes to reach a certain threshold given that the battery cells have already survived a certain amount of time (the time for the battery pack reaching the threshold). . Three-dimensional plots are used to express the quality and quantity information as a function of battery return date. The x-axis represents the battery return date, the y-axis is the expected quality indicated by remaining life, and z-axis is the quantity distribution.

2.4.1 **Quality Distribution, Q(t, x)**

Remaining useful life (RUL) is defined as a conditional random variable $X_t = T - t$ when $T > t$, where t is the time where a part has survived so far, and T is the time to failure. The conditional reliability function *Rt(t)* contains all the information required for RUL. The reliability function is defined as:

$$R_t(x) = \Pr(T - t > x \mid T > t); t, x, T \in \mathbb{R}^+ \qquad (2\text{-}15)$$

$$R_t(x) = \frac{\Pr(T - t > x) \cap \Pr(T > t)}{\Pr(T > t)} = \frac{1 - F(T + \tau)}{1 - F(T)}$$

From Equation (2-15), the failure rate of RUL *Q(t, x)* is then

$$f_t(x) = -\frac{\partial}{\partial x} R_t(x) = \frac{f(t)}{1 - F(t)} = h(t + x)R_t(x), \tag{2-16}$$

and

$$Q(t, x) = f_t(t, x) = f_t(x \mid t)f(t) = h(t + x)R_t(x)f(t), \tag{2-17}$$

where $x = T - t$, and $f(t)$, $F(t)$, and $h(t)$ are time to failure probability density function (pdf), cumulative distribution function (cdf), and hazard rate functions defined previously. The conditional distribution becomes:

$$R_t(x) = \frac{\exp\left(-\left(\frac{t + x - a}{b}\right)^c\right)}{\exp\left(-\left(\frac{t - a}{b}\right)^c\right)}, \tag{2-18}$$

and the joint probability then becomes:

$$\begin{aligned} Q(t, x) &= \frac{c}{b}\left(\frac{t + x - a}{b}\right)^{c-1} \exp\left[\left(\frac{t - a}{b}\right)^c - \left(\frac{t + x - a}{b}\right)^c\right] \\ &\quad \frac{c}{b}\left(\frac{t - a}{b}\right)^{c-1} \exp\left[-\left(\frac{t - a}{b}\right)^c\right] \quad . \\ &= \frac{c^2}{b^2}\left(\frac{t + x - a}{b}\right)^{c-1}\left(\frac{t - a}{b}\right)^{c-1} \exp\left[-\left(\frac{t + x - a}{b}\right)^c\right] \end{aligned} \tag{2-19}$$

2.4.2 **Convolution in 3D**

It is assumed that the quality is uniform when the product is initially shipped out of the factory or at the time of purchase, so the third dimension of $S(t)$ is invariant. So we have $S(t, x) = S(t)$. Similarly, because consumer's behavior will not be affected by the RUL of returned battery, their return behavior would not be affected by return time either, i.e., $C(t, x) = C(t)$. Because of this invariance in both $S(t, x)$ and $C(t, x)$, the convolution is only performed in one dimension, and it is independent of the 'quality' dimension. That means

$$f(t,\tau) * g(t,\tau) = \int_{-\infty}^{\infty} f(x,\tau)g(t-x,\tau)dx \qquad (2\text{-}20)$$

$$= \int_{-\infty}^{\infty} f(t-x,\tau)g(t,\tau)dx\ .$$

$$f, g : [0, \infty) \in ¡$$

The final result of R(t, x) is the one-dimensional convolution of S(t, x), Q(t, x), and C(t, x):

$$R(t, x) = S(t, x) * Q(t, x) * C(t, x)\ . \qquad (2\text{-}21)$$

2.4.3 **Numerical Examples**

2.4.3.1 Sales distribution, S(t, x)

Continuing the numerical example from Section 2.3.4 and the sales function are essentially the same as Equation (2-18). The 3D shape of the function is shown in Figure 2-7. It is constant in the quality direction because it is assumed the newly sold battery packs all have the same high quality. Note that the cross section is the same as the two-dimensional S(t), and it is peaked around 2 years.

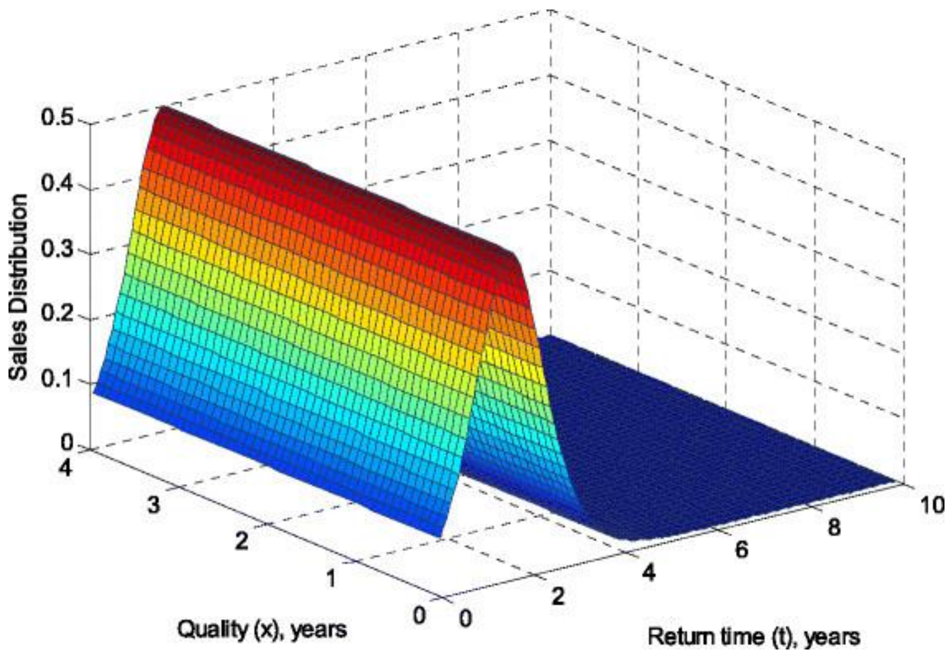


Figure 2-7. Sales distribution, S(t,x).

2.4.3.2 Quality distribution, Q(t, x)

The quality distribution is determined by two factors: the product breakdown time t and RUL x. The relationship is given by $Q(t, x)$ for this example. The shorter the product usage time t is, the longer the expected RUL x is, as in Figure 2-8. Because the mode of breakdown function $Q(t, x)$ along the t direction is around 7, the quality of returned product decreases dramatically towards zero. The peak occurs when quality is zero because majority of the cells in a battery pack is at low quality state when return.

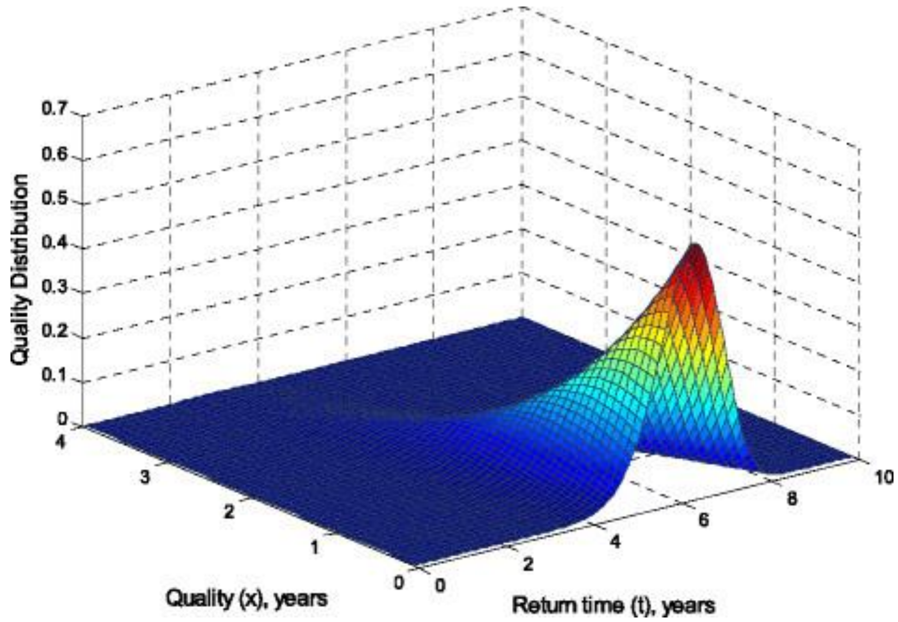


Figure 2-8. Quality distribution, Q(t,x).

2.4.3.3 Customer return distribution, C(t, x)

Similar to the sales function, the customer return behavior function is also constant along the quality axis since return behavior would not alter the quality of the product itself. That is, $C(t, x) = C(t)$, which is shown in Figure 2-9.

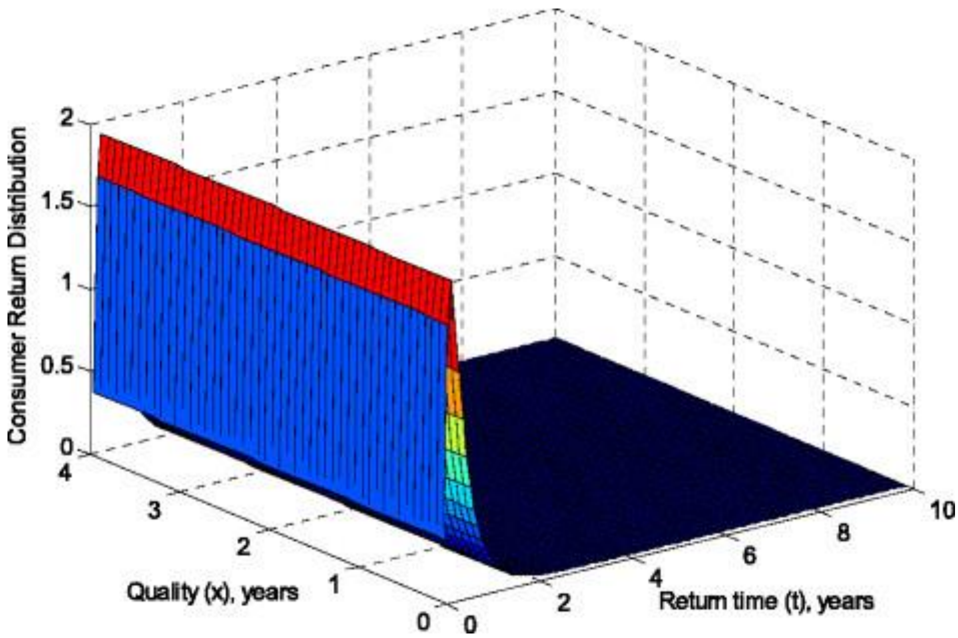


Figure 2-9. Customer return distribution, C(t,x).

2.4.3.4 Return distribution, R(t, x)

The final returned product quantity and quality plot is shown in Figure 2-10. The cross section of the plot along the time direction at $x = 0$ is the same as the $R(t)$ from numerical examples (section 2.3.4).

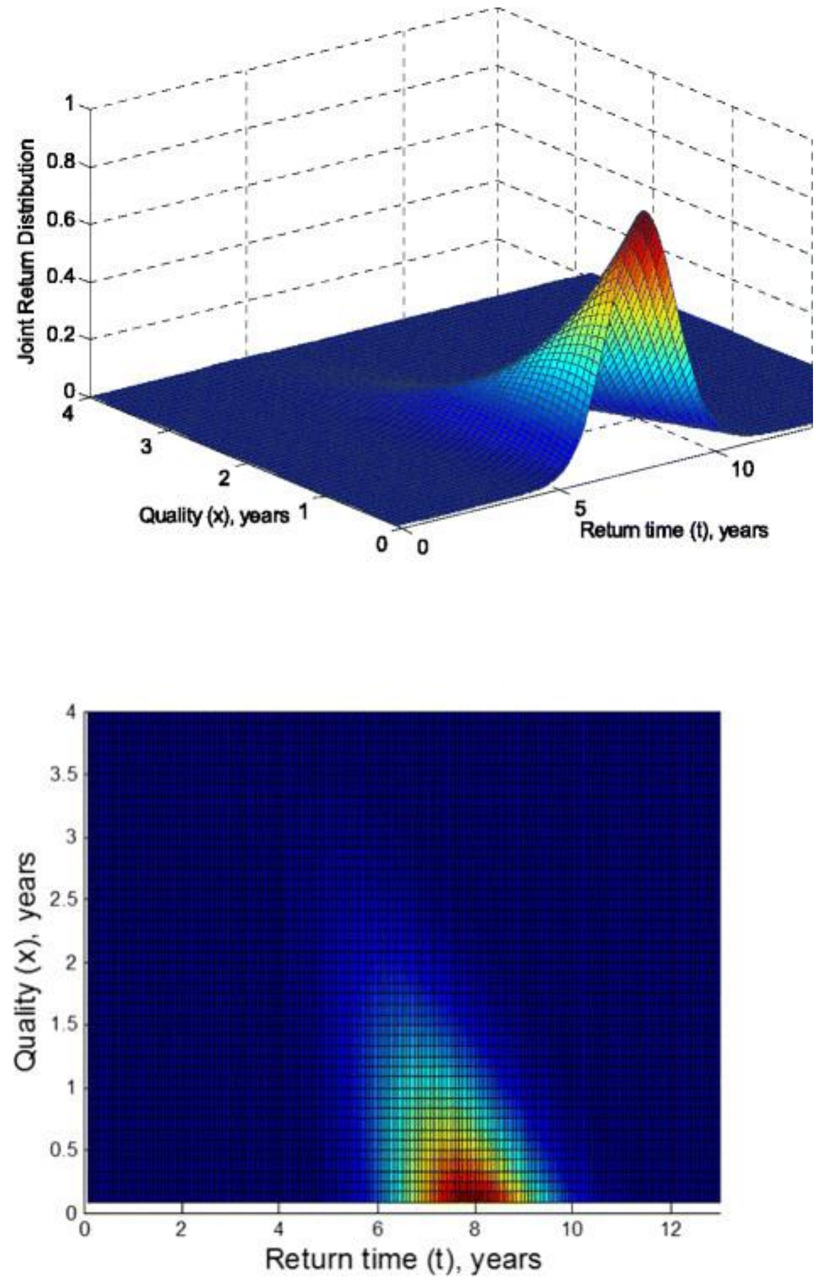


Figure 2-10. Return quantity and quality distribution, side view and top view

From this plot, it can be shown that after return date *t* passes a certain time (nine years), or the sum of peak sales date (around two years) plus peak breakdown time (around seven years), the returned products are largely in very low quality ($x < 1$ year). This gives a rough time frame of when a returned product is economical to be remanufactured. Some other end-of-life treatment, such as recycling or proper disposal, may be employed after certain time.

2.4.4 **Verification with Monte Carlo Simulation**

For this illustrative example, one million samples are used for each of the random input generation. The generation of the sales date, expected product life, and customer return behavior is the same as in the Monte Carlo simulation verification. The RUL of returned products is generated by randomly drawing samples from $Q(t, x)$ where t of each sample is determined by the expected product life samples. Therefore, whenever a sample is generated, the $Q(t, x)$ distribution needs to be recalculated. As before, $Q(t, x)$ is not normalized, so it needs to first be discretized then normalized for each sample.

Each sample has two components: the return date and return quality. Return date is calculated in the same way as in the Monte Carlo simulation verification. The return quality is sampled directly from $Q(t, x)$ as shown in the previous subsection. The distribution is obtained by using two-dimensional histogram or other scientific volume imaging techniques. The simulation results shown in Figure 2-11 agree well with $R(t, x)$ obtained using the proposed analytical convolution-based approach.

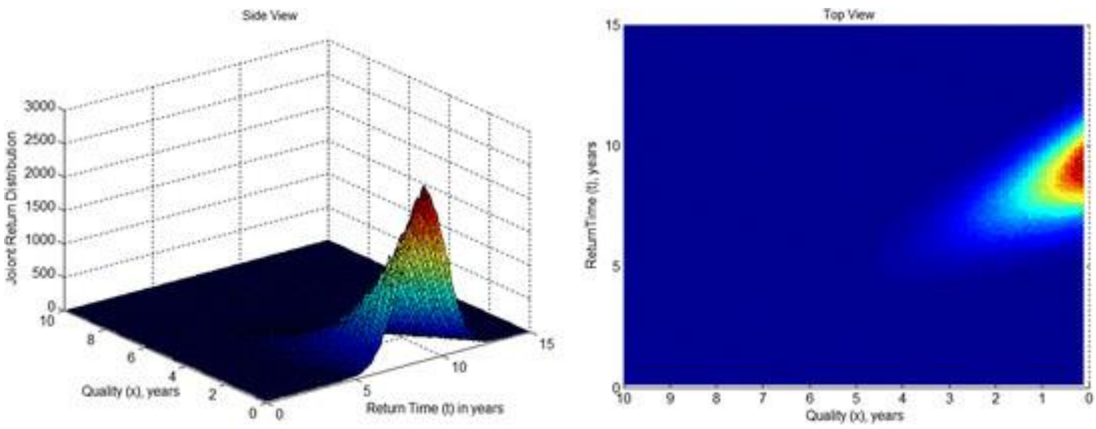


Figure 2-11. Monte Carlo for returned product quantity and quality.

2.5 Conclusions and Future Work

This research provides a methodology to forecast long-term trend of both quantity and quality of product returns, or the supply to a remanufacturing system, by modeling three major influential factors (i.e., sales, life expectancy, and customer return behavior) and their combinatory formulation in a forecasting method. To meet the emerging needs of decision support in the remanufacturing industry, reliable forecasting of supply can help determine a reasonable estimate of used products attainable under a given set of conditions and further assist decision-makings in remanufacturing operations. The effectiveness and accuracy of the forecasting model developed in this research is verified and validated with the Monte Carlo simulations.

Generally, the typical goals of strategic forecasting are threefold: (1) estimate the opportunity and outcome for future business activities, (2) find what influence and how to influence outcome, and (3) judge the potential risks associated with such business actives. The first two are covered by this research. The model developed in this research only provides the most likely outcome based on a single set of assumptions, so potential risks are more difficult to discover. Future works may include sensitivity analysis, scenario analysis, and different assumption management techniques.

CHAPTER 3

Lifecycle Warranty Cost Estimation for Electric Vehicle Battery Using an Age-Usage Based Degradation Model

3.1 Introduction

With the Honda Insight hybrid being the first electric mass production car sold in the United States in 1999, electric vehicles (EVs) have grown steadily in the US. Both technology and consumer acceptance progressed significantly over the last decades. However, the sales of EVs have not been as optimistic as people originally thought. In President Obama's 2011 State of the Union Address, he called for putting one million of EVs on the road by 2015 (Voelcker, 2011). Yet, the actual EV sales was 17,425 vehicles in 2010 and 2011 combined, 52,581 in 2012, 97,507 in 2013 and 119,710 in 2014 (InsideEVs, 2015). Percentage wise, plug-in electric vehicle (PEV) has 0.60% of the market share, battery electric vehicle (BEV) has 0.28%, and plug-in hybrid electric vehicle (PHEV) has 0.31%, which are also much below anticipated (Shahan, 2014). Because of this sluggish sales performance, some factories had to shut down or slow down their production. For instance, the GM Chevy Volt plant shut down for three months in 2012 and planned to shut down again in 2016 for two months (Autoblog.com, 2015; Radio, 2015; Pundit, 2012). Plant shutdown causes OEMs to bear a tremendous amount of overhead costs.

Among many factors that contribute to this problem, high selling price is arguably the most important one from the customers' perspective. In many cases, lowering the price can boost sales significantly. For instance, Forbes reported that after Nissan lowered the cost of its EV, the Leaf, by US$6,000 in 2013, sales jumped 18% (D Bigman, 2012). The high price problem is attributable to various factors, and production cost is one of the main factors. Out of all the components in an EV, the battery pack creates the greatest cost burden. Although the exact cost for a battery pack is confidential for most manufacturers, it is reported that a Nissan Leaf's battery pack cost as much as $18,000 to replace (E Loveday, 2010), and a Ford Focus electric version battery pack costs $12,000 to $15,000 a piece (or third of the car cost) (Ramsey, 2012). Battery alone can cost as much as a low-end compact car. Within a battery pack, the most expensive component is the battery cells. Argonne National Laboratory Center for Transportation provides a percentage breakdown for the manufacturing cost of an EV battery, where 80% are battery cell and material related (Gaines & Cuenca, 2000). Depending on the sources, the cost for Li-ion battery cells, the most popular type of EV battery, ranges from $500 to $1,000 per kWh (Urken, 2013; Hensley, Newman, Rogers, & Shahinian, 2012; King, 2012). Because of this high cost, many manufacturers sell EVs at a loss. Fiat-Chrysler stated that every time a Fiat 500e was sold, the company lost $10,000 to $14,000 (George, 2014; AutoWeek, 2011). Moreover, battery packs usually cannot last for the entire lifespan of an EV, so a second, or subsequent, battery pack is needed to continue using the vehicle. To resolve this issue, Nissan introduced a $100 per month Leaf battery replacement program (for 2^{nd} battery pack) in 2014. Therefore, both the initial purchase cost and the life-cycle cost for EVs are significantly higher than similar internal combustion engine (ICE) cars.

Due to this high production cost issue, it is critical to have a better understanding of the lifecycle battery costs and to determine possible areas where costs can be reduced in the future. There are limited numbers of lifecycle cost estimates for EVs in the literature (Price, Dietz, & Richardson, 2012; Wong, Lu, & Wang, 2011; C. Samaras & Meisterling, 2008; Jeong & Oh, 2002; Delucchi & Lipman, 2001). Their goals were to compare EV costs with standard ICE cars, so they only focused on the cost from consumer's perspective. When analyzing lifecycle costs, existing literature often focuses on car usage costs such as comparing electricity costs with gasoline costs. For manufacturers, usage costs are not their direct costs, so they may have less interest to calculate it. Many factors, such as warranties, battery pack replacement and end-of-use treatment are not included in these studies. However, they may pose a serious cost burden for manufacturers to consider.

In order to have a better understanding of the costs associated with different business models, four different types of costs are calculated. The first type is *single item cost to manufacturer*, or C_{SM}. This cost is the cost to produce a battery pack plus all the replacing/repairing costs within the warranty period, The second type of cost is *single item cost to customer*, or C_{SC}. This cost is C_{SM} plus all the replacing/repairing costs after the expiration of warranty, which denotes the customer's warranty expenses on his/her EV battery, in turn denotes the total cost to use a battery pack for the entire lifespan of an EV from a customer's perspective. In this research, the initial purchase price of an EV battery is assumed to be the sum of battery production cost, C_P and warranty cost, C_W. That is, the profit for manufacturers is neglected since many EV OEM sell cars at a loss. The reason for this circumstance is the majority of EV manufacturers are currently selling batteries at production cost or lower. The third cost is the *aggregated cost to manufacturer*, or C_{AM}. This cost is the sum of C_{SM}'s for all customers who bought certain model of EV over the entire life cycle of the product line. Finally, the fourth cost is the *aggregated cost schedule*, or $C_{AC}(t)$. This cost is the cost schedule or cost stream that manufacturers expect in each period, such as monthly or quarterly. It is considered here because most manufacturers need to allocate suitable amount of money for each period. An accurate cost estimation additionally has significant impact on many strategic decision processes for marketing, production, inventory and other areas. By comparing all four types of costs, a more comprehensive evaluation of different warranty strategies can be conducted from both manufacturer's and customer's perspectives over the entire lifespan of an EV product line.

Warranty cost estimation can be approached analytically by formulating appropriate mathematical models of the warranty process. In the literature, two-dimensional renewal processes are often used to formulate replace-only or nonrepairable two-dimensional warranties (Blischke, Karim, & Murthy, 2011a). For within-warranty failure modeling with minimal repair, non-stationary Poisson processes are generally used (Chukova & Johnston, 2006; J Baik, Murthy, & Jack, 2004). For failure modeling with imperfect repairs, delayed renewal and other stochastic process models are implemented, and other methodologies, such as "virtual age," are also used (Varnosafaderani & Chukova, 2012; Pham & Wang, 1996). Often, analytical solutions are only provided for special cases because many of them are characterized by recursive functions.

However, there are two major difficulties encountered in the analytical approaches that may not be suitable for this research. First, they are generally oversimplified, lack realism, and fail to account for many important aspects of the warranty process. Warranty is a complicated process where many steps are included, and decisions are made by both customers and manufacturers. Second, analytical approaches usually lead to intractable mathematics, complicated integrals and random processes that cannot be evaluated analytically. Therefore, Discrete Event Simulation (DES) is used for this study.

The remainder of this chapter is organized as follows. Sections 3.3.2.1 to 3.3.2.6 explain the formulation of different cost influential factors and how they may affect different types of costs. In section 3.3, the simulation model and a numerical example are illustrated. For the rest of chapter, the effects of altering different parameters are discussed. Finally, the conclusion and future research is stated.

3.2 Modeling

3.2.1 **Warranty Process**

For EV batteries, the warranties are generally considered to be two-dimensional non-renewing free replacement/repair warranties (FRW). Under FRW, if a failure or a listed dissatisfaction occurs with any part of a battery within the warranty limit, the part or the whole battery pack needs to be repaired/replaced by the manufacturer free of charge. If the replaced part fails again within the warranty period, it too will be repaired/replaced free of charge. Essentially, any failure needs to be repaired/replaced within the warranty period, and the length of warranty period is fixed regardless of the failure time, hence non-renewing.

Unlike many time-based warranties, automotive warranties normally are two-dimensional: time dimension (e.g., warranty expiration dates) and usage dimension (e.g., mileage limitations). The warranty reaches its limit whichever comes first. Such a two-dimensional warranty is defined by a rectangular region $\Omega = [0,T) \times [0,U)$, where T is the warranty expiration time, usually in years, and U is the maximum allowed car usage, usually in miles.

In order to model failures over the region Ω, two random variables are needed for both time and usage dimensions. However, this introduces much complication in modeling, so some simplification techniques are reported on in the literature to mitigate this problem. The simplest and most common method is to treat usage as a random function of age, and this function is usually called a usage rate function. Usage rate is often time-invariant over the warranty period but different across the customer population (Jaiwook Baik & Murthy, 2008; Murthy & Blischke, 2006; Iskandar & Blischke, 2003; Yang & Zaghati, 2002; Lawless, Hu, & Cao, 1995). In this research, the usage and age are assumed to have a linear relationship. Let $R(t)$ be a random variable representing usage rate at time t derived from the usage $U(t)$, and the usage time $T(t)$. The usage rate is also assumed to be constant throughout the entire lifespan of the EV, beyond the normal warranty period, as shown in Figure 3-1. Let $R(t)$ denote a non-decreasing process of the battery usage written as following:

$$R(t) = U(t) / T(t) . \tag{3-1}$$

For simplicity, $R(t)$ is assumed to be a constant over the entire lifespan of the EV, denoted as Λ and indicated by the red lines. Note that λ is a realization of the random variable Λ because it can vary across population. For different customers, λ can be different. Conditioning on r, the effective warranty period (EW) becomes:

$$EW = \min\{T_0, U/r\}, \tag{3-2}$$

where T_0 is a fixed warranty expiration date.

The EW is calculated as the minimum of the time until the warranty expires and usage warranty limits. Actual usage rate can vary daily, as illustrated by the blue curves. This assumption is also applied in (Jaiwook Baik & Murthy, 2008; Murthy & Blischke, 2006; Iskandar & Blischke, 2003; Yang & Zaghati, 2002; Lawless et al., 1995). It can also be seen from the figure that for the low usage rate case, the effective warranty period is defined by the time expiration date, T_0. For the high usage rate case, it is defined by usage limit, U. By implementing this way, the failure time, failure rate and reliability function in next several sections can also be expressed by using only the usage rate, λ.

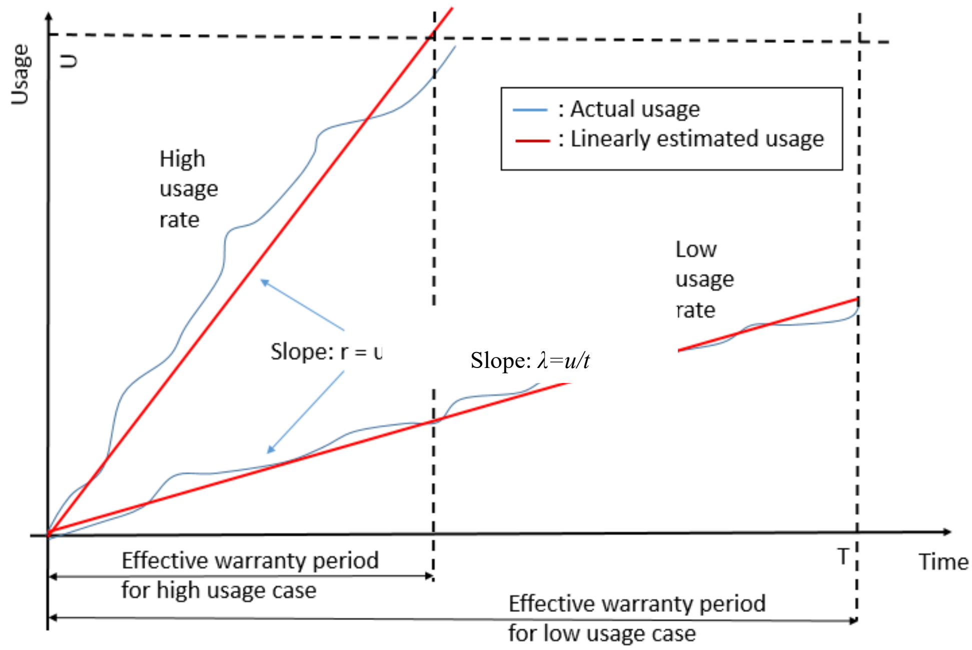


Figure 3-1. Examples of battery degradation with high and low usage rates and age limits.

3.2.2 **Usage Rate**

The amount of daily driving varies from person to person. There have been some studies conducted on driving range in the U.S. in the past 5 years to determine driving range needed for different types of EVs (Smart, Powell, & Schey, 2013; K. Smith, Earleywine, Wood, Neubauer, & Pesaran, 2012; Pearre, Kempton, Guensler, & Elango, 2011; Majeske, 2007). Averaging the above four data sources, the usage rate (daily), R is best fitted with a Gamma distribution with probability density function

$$f(r) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} r^{\alpha-1} e^{-r/\beta}, \quad \text{where } \alpha = 3.24, \beta = 10.9$$

$$f_R = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \Lambda^{\alpha-1} e^{-\Lambda/\beta} \quad , \qquad (3\text{-}3)$$

where the parameters $\alpha = 3.24$ and $\beta = 10.9$ are based on (Majeske, 2007). The mean value and variance of the usage rate are 35.3 and 384.9 respectively, as shown in Figure 3-2. If the battery warranty is the standard 8 years and 96,000 miles, the EW is shown in Figure 3-3.

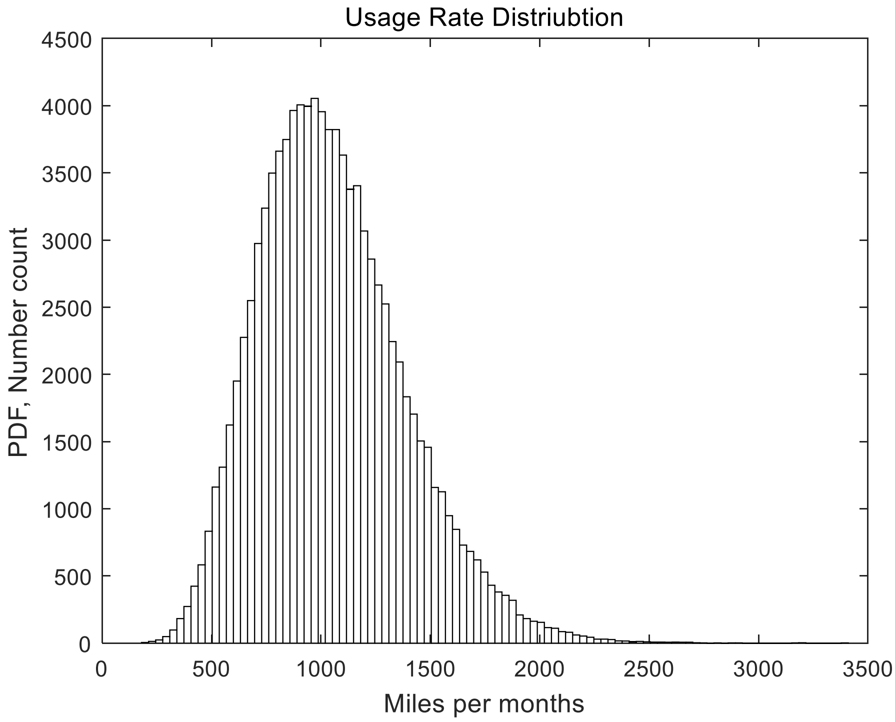


Figure 3-2. Usage rate distribution.

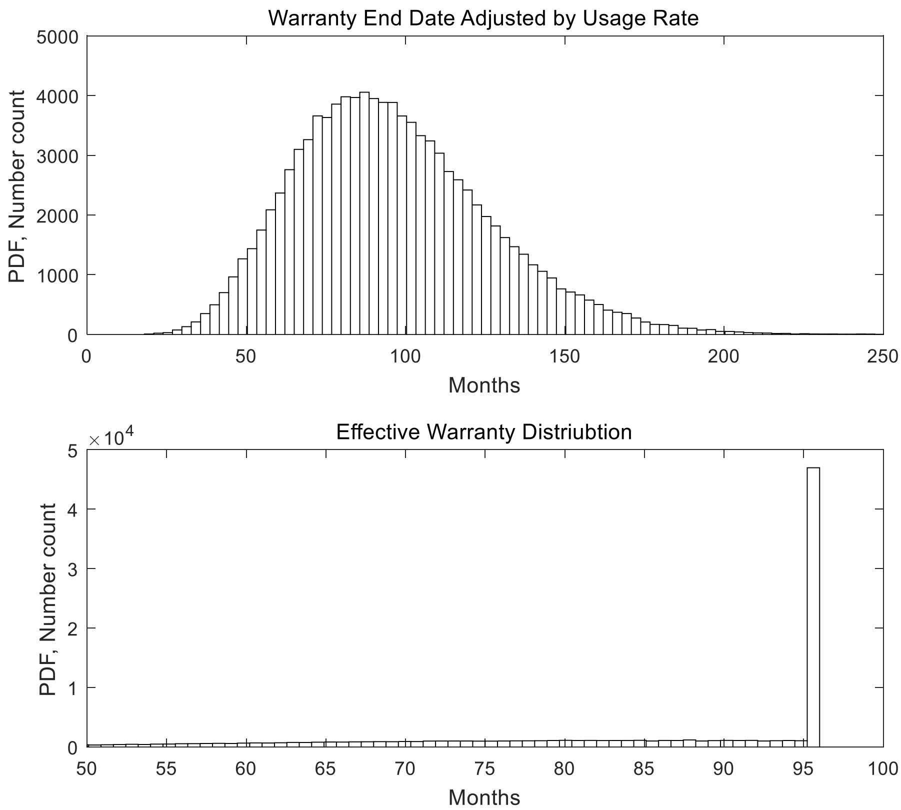


Figure 3-3. Effective Warranty (EW) distribution where EW< 8 years (top) and the entire EW distribution (bottom).

3.2.3 **Reliability-Centered Battery Degradation Model**

The Li-ion battery aging mechanism has been studied extensively in the past decade. Many efforts have been devoted to physics-based model including electrochemical model, equivalent circuit model, and others. However, data driven methods such as reliability function or statistical failure behavior are generally unknown because it requires a large number of run-to-fail battery test data. Unfortunately, most of the degradation data for commercial EV battery packs are confidential for EV OEMs. Reliability functions generally are inferred from either known degradation processes or real measured condition metrics, such as crack size, loss of efficiency and others. In this research, the degradation processes of the Li-ion battery can be modeled using existing techniques, such as first hitting threshold time (FHTT), to transfer the physics-of-failures (PoF) to reliability functions (Letot & Dehombreux, 2009; Lee & Whitmore, 2006; Van Noortwijk, Kallen, & Pandey, 2005; Ting Lee, Whitmore, Laden, Hart, & Garshick, 2004). Once a base reliability function is developed for average drivers with an average usage rate, an Accelerated Failure Time (AFT) model is used to extrapolate the base reliability function to drivers with different usage rates. It is also assumed that the degradation process is only influenced by time and usage. Other causes, such as operating temperature, state of charge for each cycle, charge protocols, and driving patterns, are not considered in this research.

If τ is a random variable representing failure time, the reliability function and its complementary, failure functions, are:

Reliability function: $$R(t) = \Pr(\tau > t) \tag{3-4}$$

Failure function: $$F(t) = 1 - R(t) = \Pr(\tau < t) \tag{3-5}$$

Failure density function: $$f(t) = \frac{dF(t)}{dt} = -\frac{dR(t)}{dt} \tag{3-6}$$

Failure rate function: $$\begin{gathered} h(t) = \frac{f(t)}{R(t)} = \frac{f(t)}{1 - F(t)} \\ R(t) = \exp\left(-\int_0^t h(u)du\right) \end{gathered} \tag{3-7}$$

To obtain $R(t)$, a degradation process of battery capacity $Z(t)$ and the threshold of end-of-life condition z_c are needed. More specifically, $Z(t)$ is the average Li-ion battery capacity loss at $30°C$ (Dubarry et al., 2011; Sarre, Blanchard, & Broussely, 2004; Broussely et al., 2001). We assume that the full capacity of battery has a range of 200 miles at a usage rate of 35 miles/day. This means a charging cycle is 5 days. z_c is set to be at 20% loss. There are several different kinds of failures that will be explained in detail in the next section. The failure here is a "soft failure" that is defined as the total capacity of a battery is below 80% of its capacity. The degradation process is assumed to be a Gaussian degradation process or a standard Wiener degradation process with an exponential trend, and it is simulated as in Figure 3-4.

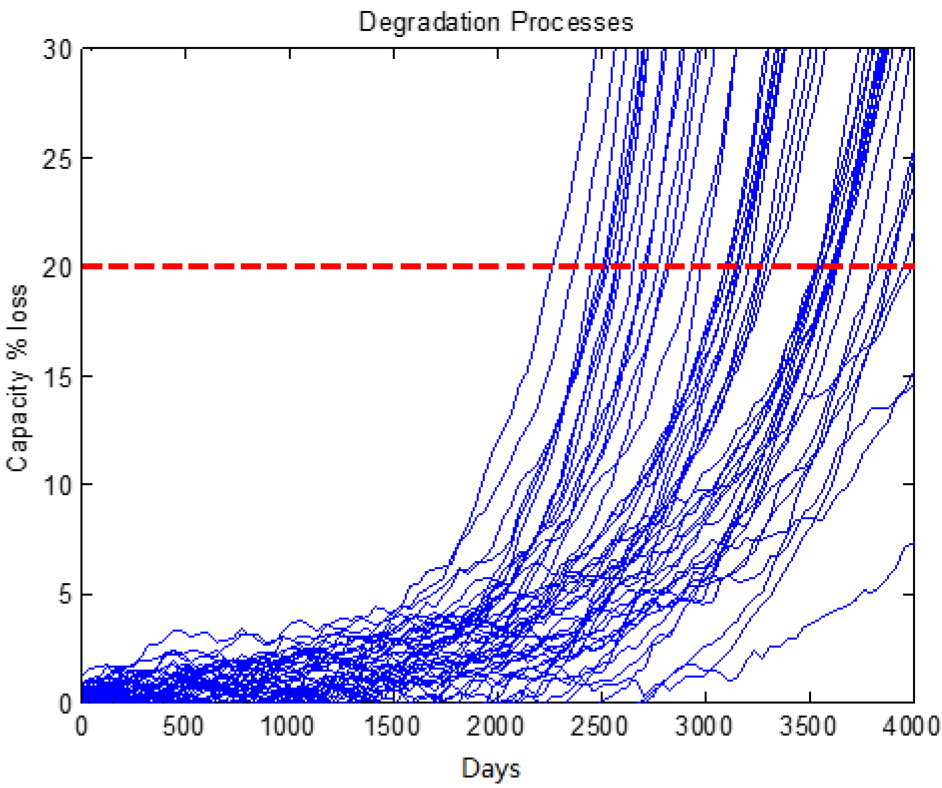


Figure 3-4. Simulation of degradation processes with threshold = 20%

From the above setting, the first hitting time, T_c, to reach the critical threshold is:

$$\begin{aligned} T_C &= \inf\{t \mid Z(t) \geq z_C\}, \\ \text{where } Z(t) &= Z(0) \end{aligned} \quad (3\text{-}8)$$

where *a* and *b* are trend scale and shape factors, σ is the drift, and *W(t)* is a Wiener process. Then, the reliability can be expressed as

$$R(t) = \Pr(T_C > t) = \Pr(Z^{-1}(z_C) > t), \quad (3\text{-}9)$$

where $Z^{-1}(\cdot)$ is the inverse of $Z(\cdot)$. The inverse function is difficult to obtain analytically, so simulation is used instead. Weibull distribution turns out to have the best goodness-of-fit for the simulated data, and it has the following form:

Reliability function: $$R(t) = e^{-(t/\lambda)^k} \quad (3\text{-}10)$$

Failure function: $$F(t) = 1 - e^{-(t/\lambda)^k} \quad (3\text{-}11)$$

Failure density function: $$f(t) = \frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1} e^{-(t/\lambda)^k} \quad (3\text{-}12)$$

Failure rate function: $$h(t) = \frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1} \quad (3\text{-}13)$$

where $k > 0$ is the shape parameter and $\lambda > 0$ is the scale parameter of the distribution. For this particular example, $k = 19.89$ and $\lambda = 2738$.

3.2.4 **Influence of Usage**

The reliability functions above are for nominal usage intensity, or 35 miles/day. Reliability functions can also vary across different usages groups. Intuitively, the more intensively people drive, the sooner the battery will fail. The most widely used methods to extrapolate the reliability function to different customer groups are Accelerated Failure Time (AFT) model and Proportional Hazard Model (PHM). They are similar to each other, and one can translate to another. The major difference between these two is that AFT assumes that the time-to-failure under stress depends on the base time-to-failure and a stress function, and PHM assumes that the new hazard function is the product of the base hazard function and a stress function. The AFT approach was chosen here because of its easier formulation when time-to-failure is more relevant in this research. Formally, let T_s denote the time-to-failure under stress s, and T_0 denote the base time-to-failure under nominal stress. Here, s is the ratio of the nominal 35 miles/day usage rate to the actual individual usage rate λ, i.e., $s = 35/\lambda$. Then the AFT model is the following:

$$T_s = T_0\phi(s), \tag{3-14}$$

where $\phi(s)$ is

$$\phi(s)\begin{cases} > 1, & \text{when } s > 1 \\ = 1, & \text{when } s = 1 \\ < 1, & \text{when } s < 1 \end{cases} \tag{3-15}$$

and is a non-negative and monotonically increasing function. Here, a linear relationship is assumed, or the time is simply scaled according to the stress *s*. The reason is that time-to-failure is proportionally dependent on charging cycle, and charging cycle is also proportionally dependent on driving amount. This implies

$$\begin{aligned} T_S &= T_0 s \\ R_S(t) &= R_0(st) \end{aligned} . \tag{3-16}$$

3.2.5 **Replacement and Repair**

In literature, there are generally three types of repair or replacement policies according to how failure rate may change after a repair/replacement: minimal repair (MR), imperfect repair (IR) and complete repair or replacement (CR) (Blischke, Karim, & Murthy, 2011b). For MR, the failure rate after the repair is essentially the same as that if the item had not failed. IR is often associated with restoration factors. For restoration factor of 100%, a component is as good as new. On the other hand, a restoration factor of zero implies that the component is the same as at the failure state. IR is often modeled as reduction in failure rate directly or reduction in "virtual age." The virtual age is often calculated from the reliability function. Unlike some literature, the IR here always restores battery to a better condition. For this research, the failure rate function after IR is randomly chosen between brand new condition and the condition right before the repair. CR is the same as replacement, which means the battery will restore to a like-new state, and the failure rate will also be reset to the lowest level.

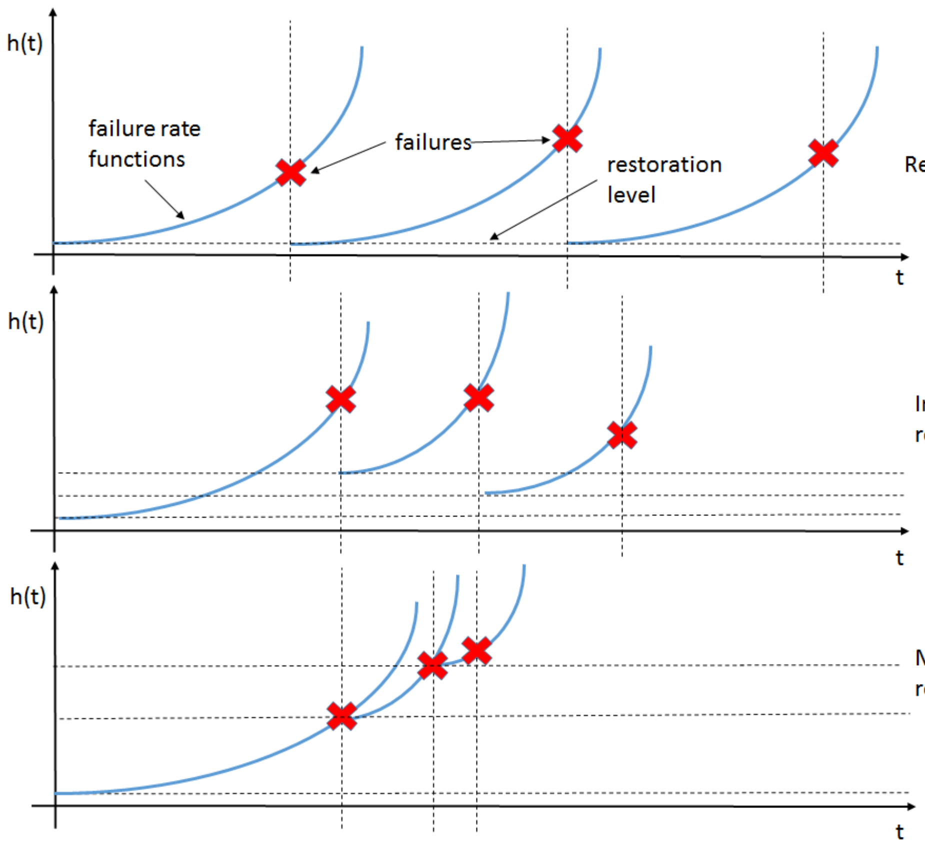


Figure 3-5. Failure functions for replacing, imperfect repair and minimal repair.

A battery pack is a complex system, and all three types of repair/replace strategies are used, as illustrated in Figure 3-5. Replacement is applied to the entire battery pack and after each the failure function is renewed. MR is used for replacing any electronics in a battery pack, such as battery management system (BMS). IR is for replacing single battery modules to reset the battery degradation process at the battery pack level. This causes a slight alteration from the classic sense of MR and IR because only a subsystem is repaired or replaced. To estimate the reliability function for the whole system after the repairing/replacement, conditional Weibull distribution is used. Conditional Weibull distribution characterizes the reliability function given that the system has already survived for certain period of time. It is formed by applying simple Bayesian theorem to the original Weibull distribution. If t_f denotes the failure time, the reliability function after the failure at time t becomes the reliability function:

$$R(t \mid t_f) = e^{[(t_f/\lambda)^k - (t/\lambda)^k]}. \tag{3-17}$$

Table 3-1. Characteristics of different types of repairs.

Repair types	Cause	Reliability function	Condition after repair
Replacement	Physical degradation	Weibull distribution	Like new, reset degradation process
Minimal repair	Electronics failures	Exponential distribution	Same as before repaired, degradation process does not change
Imperfect repair	Single module problems	Uniform distribution	Improved condition, randomly set degradation process

For model simplicity, all repairing and replacing times are ignored since they are negligible compared to battery degrading time. Furthermore, subsystem failures do not affect the rest of the battery pack, so the reliability function after MR and IR only changes the "initial condition", not the internal parameters, such as λ and k.

3.2.6 **Sales Prediction Model**

There are generally two approaches for sales prediction when there is limited historical data: *aggregated* and *disaggregated* models. An aggregated model usually works in a top-down approach such that only the cumulated behavior of a group of people is studied. On the other hand, disaggregated models study individual decision makers that underlie market demand or supply and integrate them. Although the emphasis in forecasting and econometrics has generally shifted from aggregated to disaggregated models in the past decades, most forecasting models used in industry today are still of the aggregated form simply due to the difficulty and expense of collecting data on individual consumers. Out of all the aggregated models, *Bass Diffusion Model* is the most often used (Mahajan et al., 1995).

Mathematically, the basic format is a *Riccati* equation with constant coefficients. The differential equation has the following form

$$\frac{f(t)}{1-F(t)} = p + qF(t), \tag{3-18}$$

where $F(t)$ is the base function, $f(t)$ is the rate of change or derivative of $F(t)$. p is the coefficient of early adopters, advertising effect, or innovators in Bass's original model. It describes how quickly early adaptors are willing to purchase or to enter a new market. q is the coefficient of followers, internal influence, word-of-mouth effect, or imitator's factors in the original model. Sales volume at time t, $S(t)$, is the rate of change of installed base $f(t)$ multiplied by the market potential, *m*, and has the form of

$$S(t) = mf(t). \tag{3-19}$$

The solution to equation (3-19) is

$$S(t) = m\frac{(p+q)^2}{p}\frac{\exp(-((p+q)^t))}{(1+q/p\exp(-((p+q)^t)))^2}. \tag{3-20}$$

where the time of peak sales t^* is:

$$t^* = \frac{\ln q - \ln p}{p+q}$$

In practice, $p > q$ since early adopters usually act much quicker than followers. The choice of p and q depends on many other social factors and industry (Lilien & Rangaswamy, 2004). Here, n is only a scale that changes t from years to months ($n = 12$) or days ($n = 365$).

3.2.7 **Simulation Model**

Discrete event simulation is used to simulate a discrete sequence of events.

In particular, car purchase, degradation, failures, repairs, end of warranty, and other parameters, can all be viewed as discrete events that take place in a time sequence. If a failure occurs within the two-dimensional warranty period, the manufacturer is going to pay the repair/replace cost in full. After the expiration of the warranty, the customers pay all the costs. At the end of the simulation, statistics of different costs incurred during the selected period of time are collected for analysis. Figure 3-6 illustrates the simplified flowchart of the discrete event simulation for a single battery pack. For the entire product line, 100,000 samples are simulated. In particular, 100% of diagnosis rate is assumed. That is, all the failure diagnosis is assumed to be correct. All the diagnosis time and repairing/replacing time is assumed to be zero.

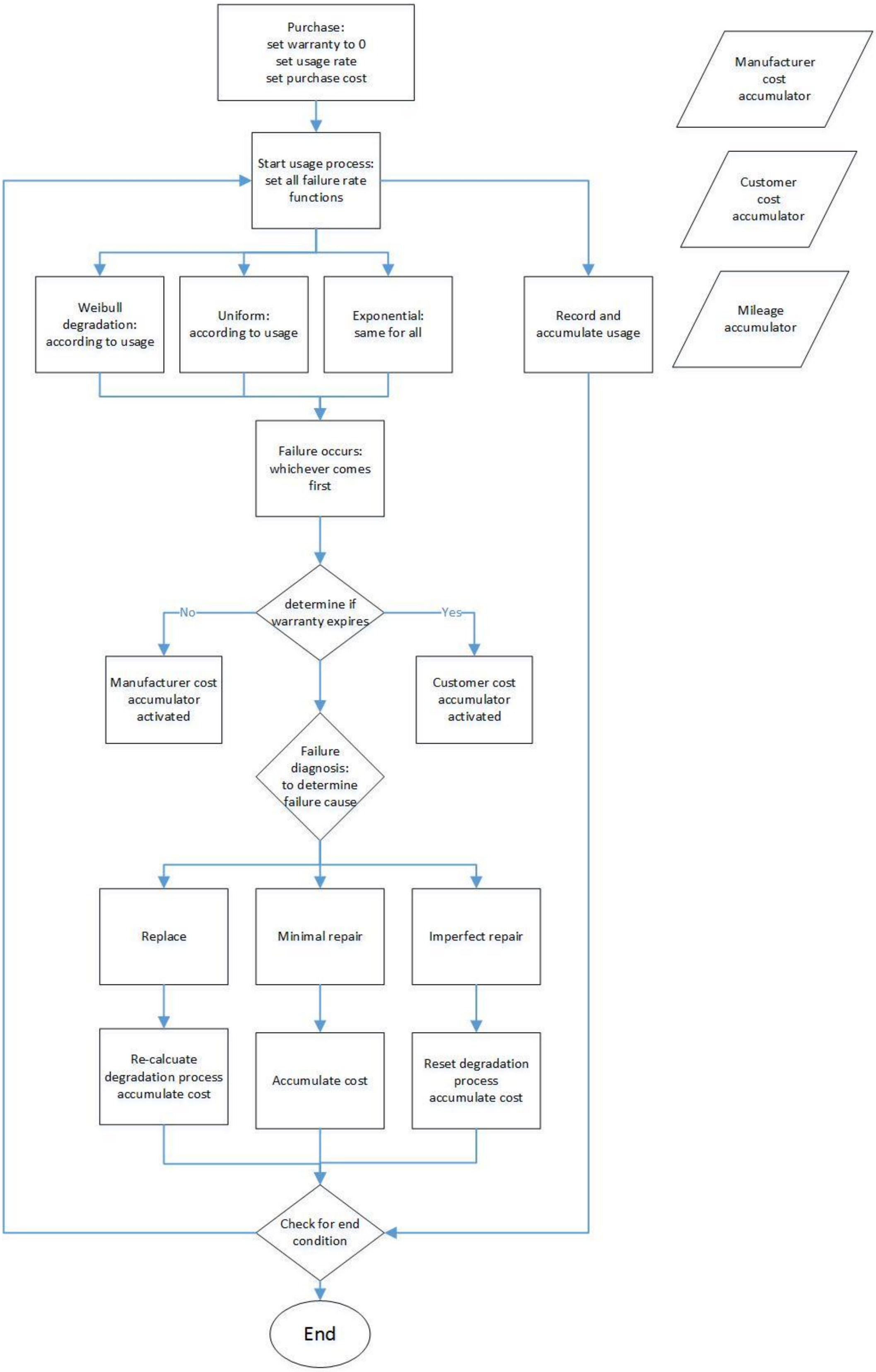


Figure 3-6. Simplified flow chart of current practice for a single customer

3.3 Numerical Case Study

3.3.1 **Parameters**

This section presents a numerical study on the developed methods for the EV battery application. One of the difficulties for this study is the lack of information and data because most of the costs and reliability distribution parameters are confidential for most EV companies. In this research, various cost parameters are set based on related knowledge and referenced studies as described in this section. Table 3-2 lists all the parameters and the associated value and description used for the simulation.

Table 3-2. List of parameters.

Notation	Value	Description
N	100,000	Number of EVs sold
C_N	\$10,000	Cost of a new battery pack, also the replacing cost
C_{MR}	\$1,000	Cost of a minimal repair
C_{IR}	\$2,000	Cost of an imperfect repair
T, U	2920 days (8 yrs), 100,000 miles	Warranty coverage, same as 2014 Nissan Leaf (the most popular EV)
L, M	5475 days (15 yrs), 200,000 miles	Life span, consumers will replace the car after 15 years or 200,000 miles
α, β	3.24, 10.9	Gamma distribution parameters for usage distribution, mean is 35 miles
λ, k	2737 days (7.5 yrs), 25	Weibull distribution parameters for degradation process They are obtained from the life testing data, i.e., the mean life expectancy is about 7.5 years and standard deviation is 1 year
μ	18250 days (50 yrs)	Exponential distribution parameter, failure

		rate is $\lambda = 1/\mu$
a, b	0, 18250 days (50 yrs)	The lower and upper limits of the uniform distribution
m, n, p, q	$m = 1,\ n = 365$ $p = 0.08,\ q = 2$	The parameters of the Bass diffusion model for sales prediction

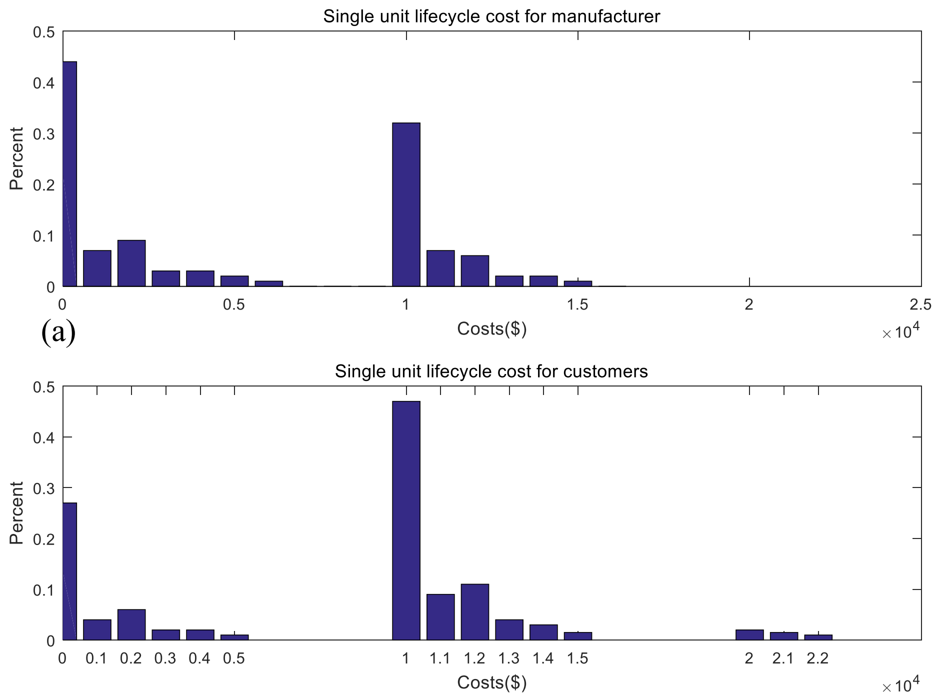
3.3.2 **Results**

The cost results are summarized in Table 3-3. A manufacturer pays every repair/replacement during the warranty period and customers pay any fees beyond the warranty. It is reasonable to assume that each battery pack may have no failure, fail once or up to twice during its warranty period or after the warranty period. As it can be seen, most of the costs are paid by customers.

Table 3-3. Simulation results

	Percentage of the time (%)		
	No failure	**Once**	**Twice**
No. of replacements paid by manufacturer	60.07	39.93	0
No. of min. repairs paid by manufacturer	86.73	12.44	0.83
No. of imp. repairs paid by manufacturer	86.66	12.31	1.03
No. of replacements paid by customers	33.99	65.39	0.62
No. of min. repairs paid by customers	87.77	11.43	0.80
No. of imp. repairs paid by customers	85.17	14.14	0.69
Costs	**Mean ($)**	**Min ($)**	**Max ($)**
C_{SC}, single unit lifecycle cost for customer	17,104	10,000	23,000
C_{SM}, single unit lifecycle cost for manufacturer	4,421	0	16,000
C_{AM}, aggregate cost for manufacturer	$442.1 Million		

From the cost histogram (Figure 3-7), the final costs are “grouped” according to the number of replacements during the warranty period and after the warranty periods. For the manufacturer’s costs, one group is from \$0 to \$2000, and another group is from \$10,000 to \$12,000. For the aggregated cost schedule, the date of sale for each car is generated according to the Bass Diffusion Model. The resulting data is provided in Figure 3-8. Usage and repair/replace simulation is essentially the same as above. A quarterly schedule is additionally used here because the plans for manufacturers are usually made quarterly. Figure 3-9 shows how many replacements, minimal repairs and imperfect repairs are expected in each quarter. The resulting cost schedule can be seen in Figure 3-10.



(b)

Figure 3-7. Histogram of lifecycle costs for (a) manufacturer, (b) customer.

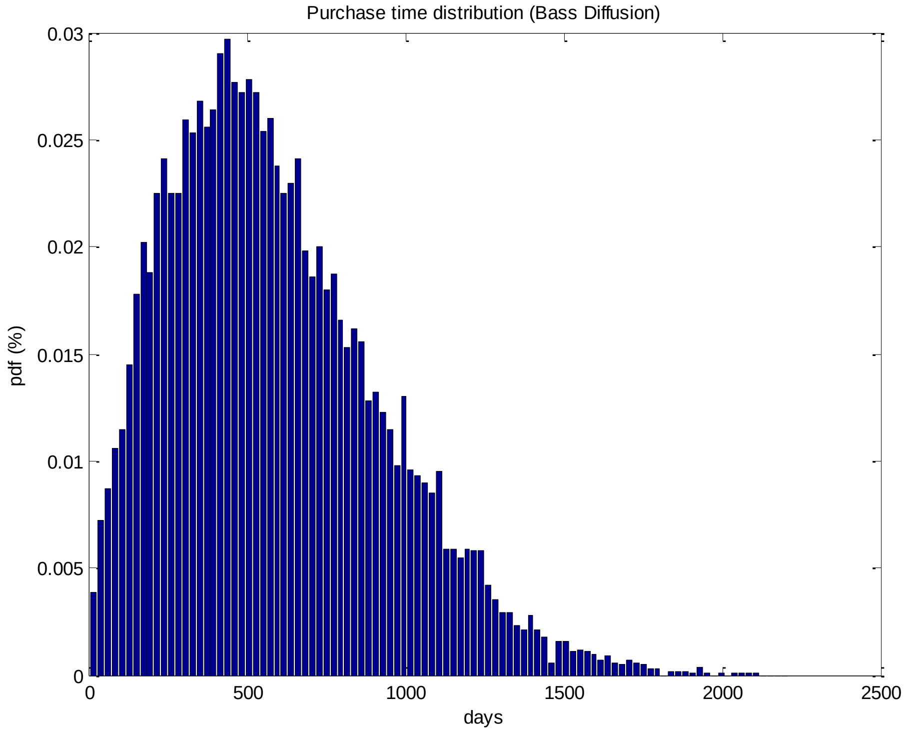


Figure 3-8. Probability density function of predicted sales using Bass diffusion model.

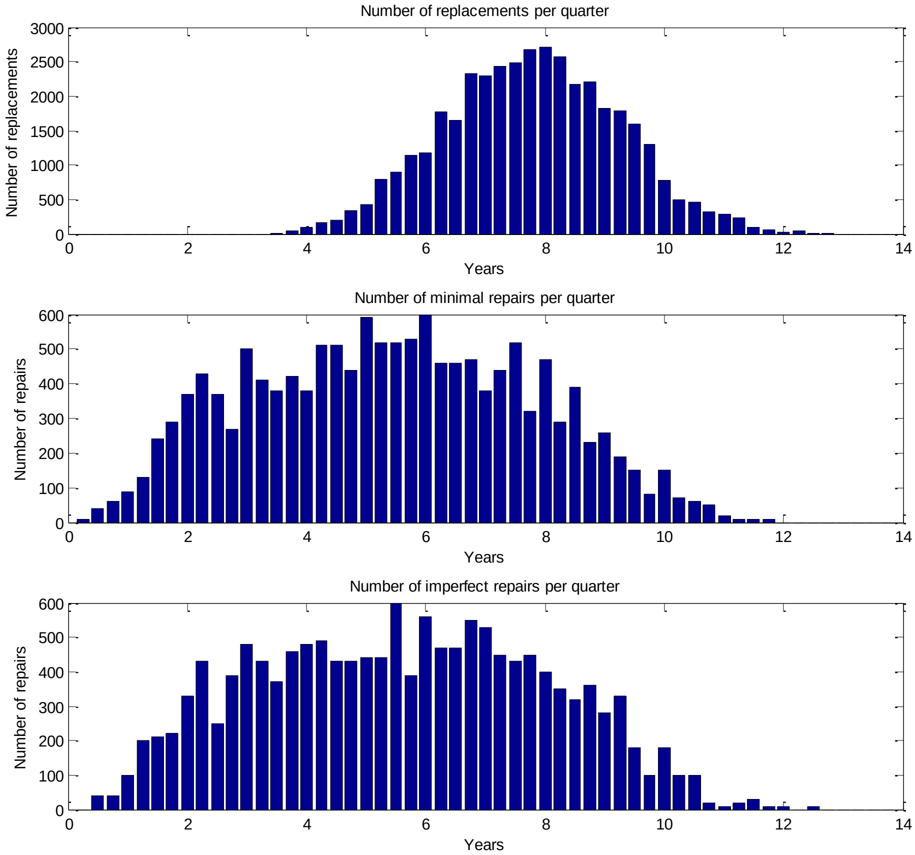


Figure 3-9. Failure schedule for manufacturer for replacements, minimal repairs and imperfect repairs.

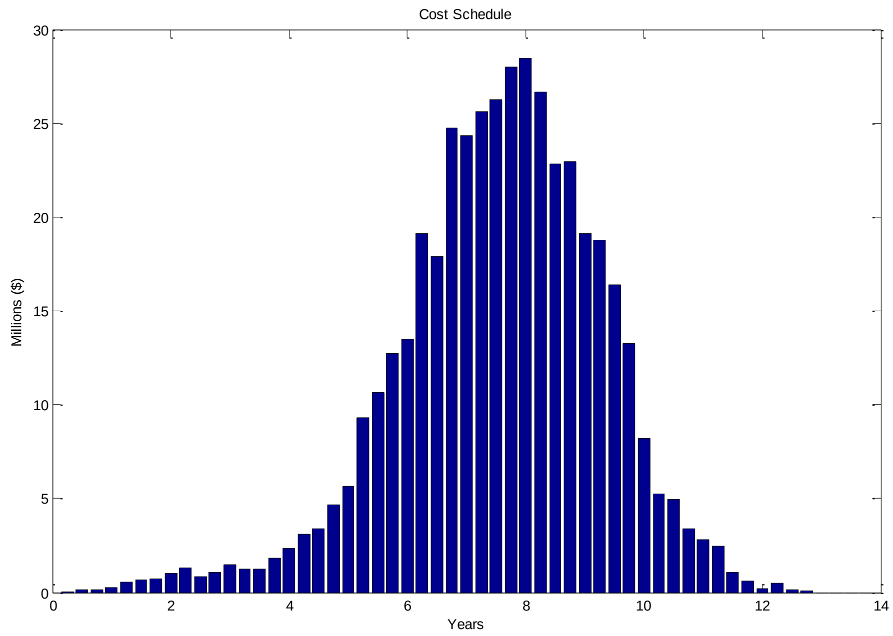


Figure 3-10. Cost Schedule for manufacturer.

3.3.3 **Effects of Altering Battery Reliability and Warranty Period**

In the automotive industry, warranty is usually treated as a marketing tool. For customers, longer warranty periods usually signal better quality or the willingness to improve the product. Many EV companies also utilize this marketing tool to increase their sales. For instance, Tesla increased the battery warranty for Model S three times from 2011 to 2014. It can also be seen in marketing and business literature. However, the quality assurance aspect of warranty is rarely seen in engineering literature. For this research, it is also assumed that changing of warranty terms has no effect on consumer purchasing behavior.

Due to the computational intensive nature of the simulation, the sample size or the number of customers is assumed to be 10,000 for each case study. The final total cost is then increased 10 times to simulate 100,000 customers. It is also assumed that the proportion between time dimension of the warranty and usage dimension is constant. That is, it is always assumed 1,000 miles per month or 12,000 miles per year, which is the industry standard. For example, a ten-year warranty also has a 120,000-mile limitation, and a five-year warranty only has a 60,000-mile limitation. This, the percentage of drivers who will reach the time warranty limit or mileage limit will be the same throughout this section. Furthermore, the distribution of usage rate is the same. Only the baseline reliability function will change; the number of batteries above or below the baseline will remain the same. It is also assumed that the lifecycle is 15 years or 180,000 miles.

Figure 3-11 shows on average how much customers need to pay during the entire battery lifecycle when the warranty limit and reliability function are varied. Similarly, Figure 3-12 shows how much the manufacturer needs to pay, and Figure 3-13 shows the total money that the customer and manufacturer combined need to pay. Note that the total cost is independent of warranty because it only depends on the number of failures.

From a customer's perspective, there is a huge incentive to choose a battery with long warranty. If the true reliability is unknown to them, they may pay more than $30,000 when the warranty limit is short, and approximately $10,000 (the initial battery cost, no repair/replace cost) when the warranty limit is long. On the other hand, the manufacturer is more likely to choose a warranty limit as similar as the mean breakdown time to minimize the cost it needs to pay. This creates conflict between customers' incentive and manufacturer's incentive due to unbalanced knowledge about the true battery reliability function.

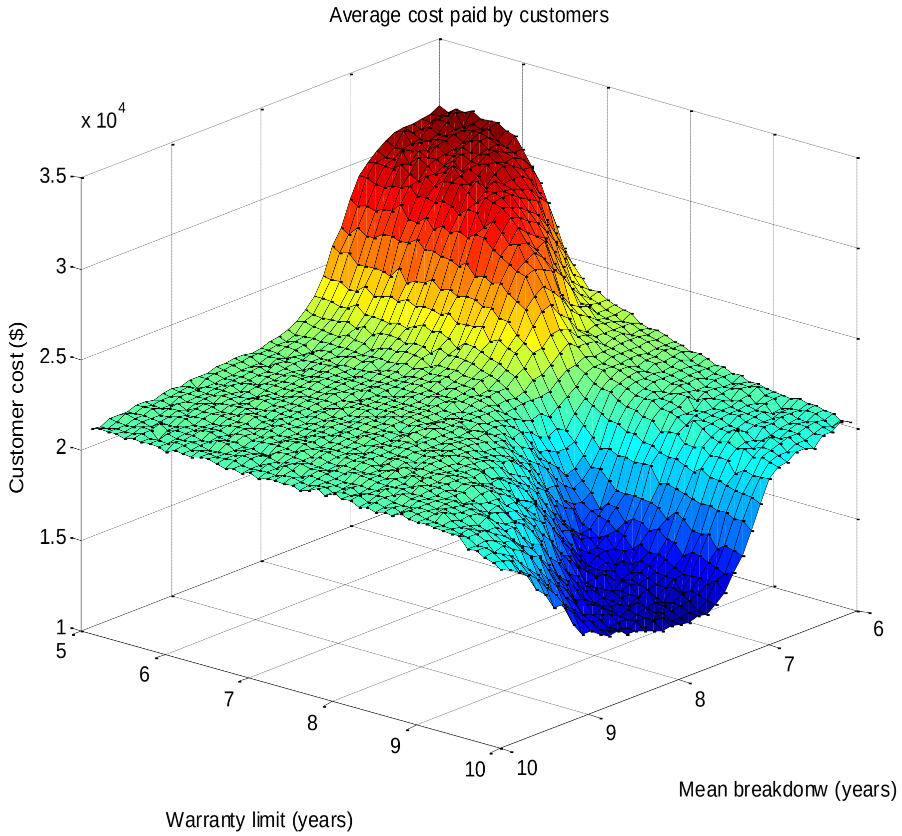


Figure 3-11. Average cost paid by customers with varying warranty and breakdown time.

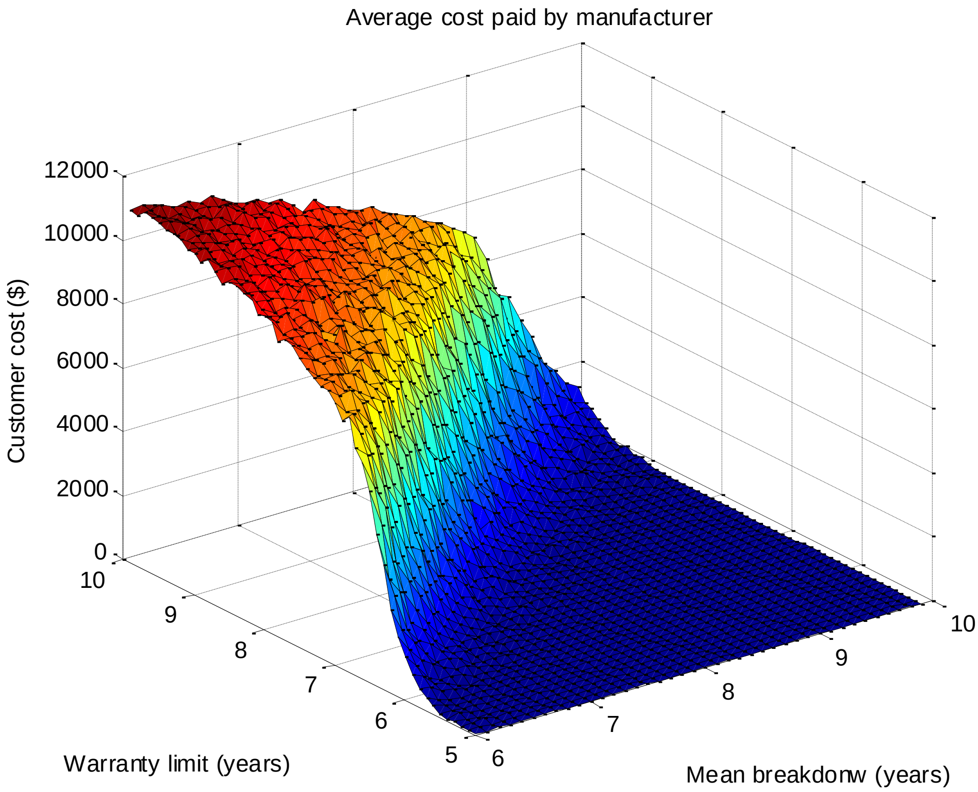


Figure 3-12. Average cost paid by manufacturer with varying warranty and breakdown time.

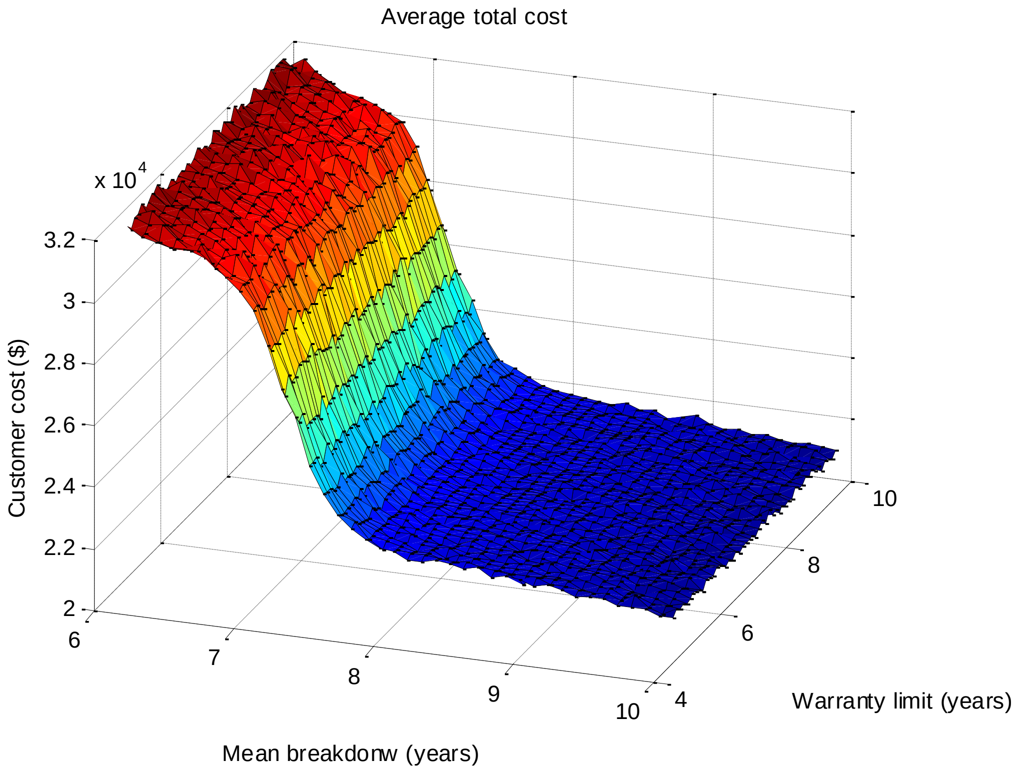


Figure 3-13. Average total cost when warranty and reliability functions are varied.

For the aggregated cost schedule, $C_{AM}(t)$, Figure 3-14 shows when keeping reliability function the same and only changes warranty limit. When warranty limit is shorter than the mean breakdown time, most batteries don't break during the warranty period. This is due to the standard deviation for the base reliability function is set around 1. When warranty limit is longer than the mean breakdown time, the cost schedule is about the same. This is also due to relatively small standard deviation for the reliability function and also the "grouping" effect seen in Figure 3-7. During this time, most failures are covered by the manufacturer, not by customers. Figure 3-15 shows the cost schedule is very sensitive to warranty change. Even 0.2-year increments in warranty limit can result in a drastic change in the cost schedule (y-axis).

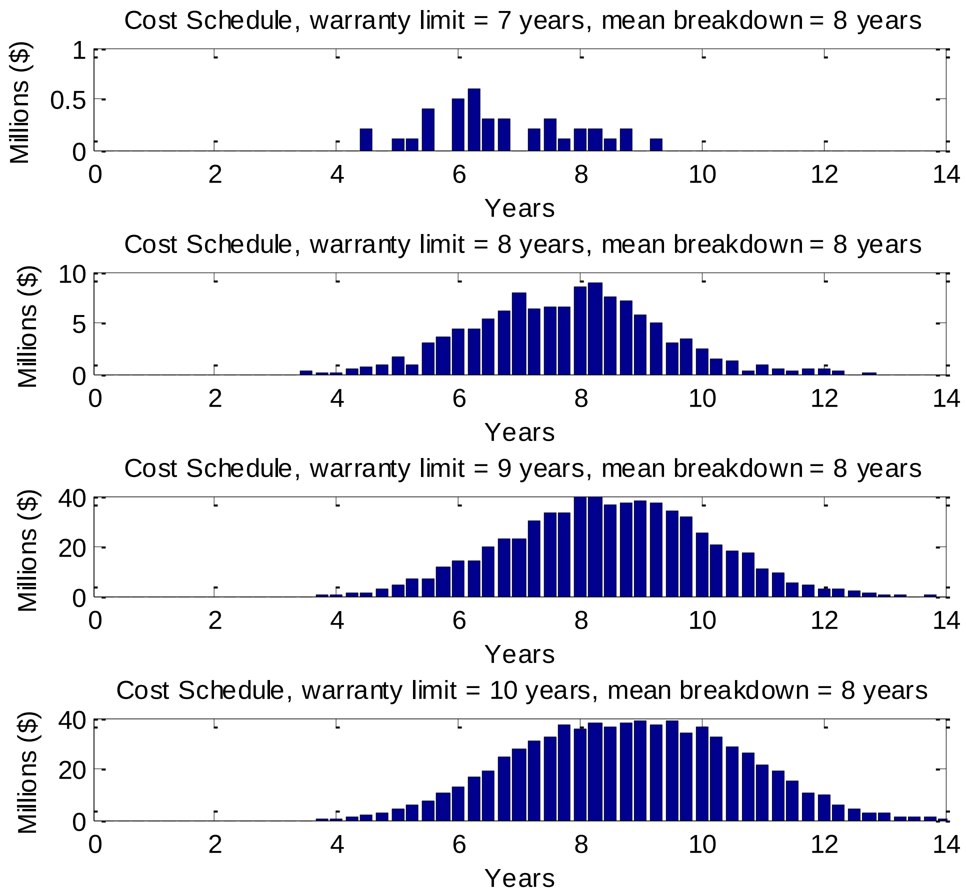


Figure 3-14. Cost schedule when reliability remains constant and warranty changes.

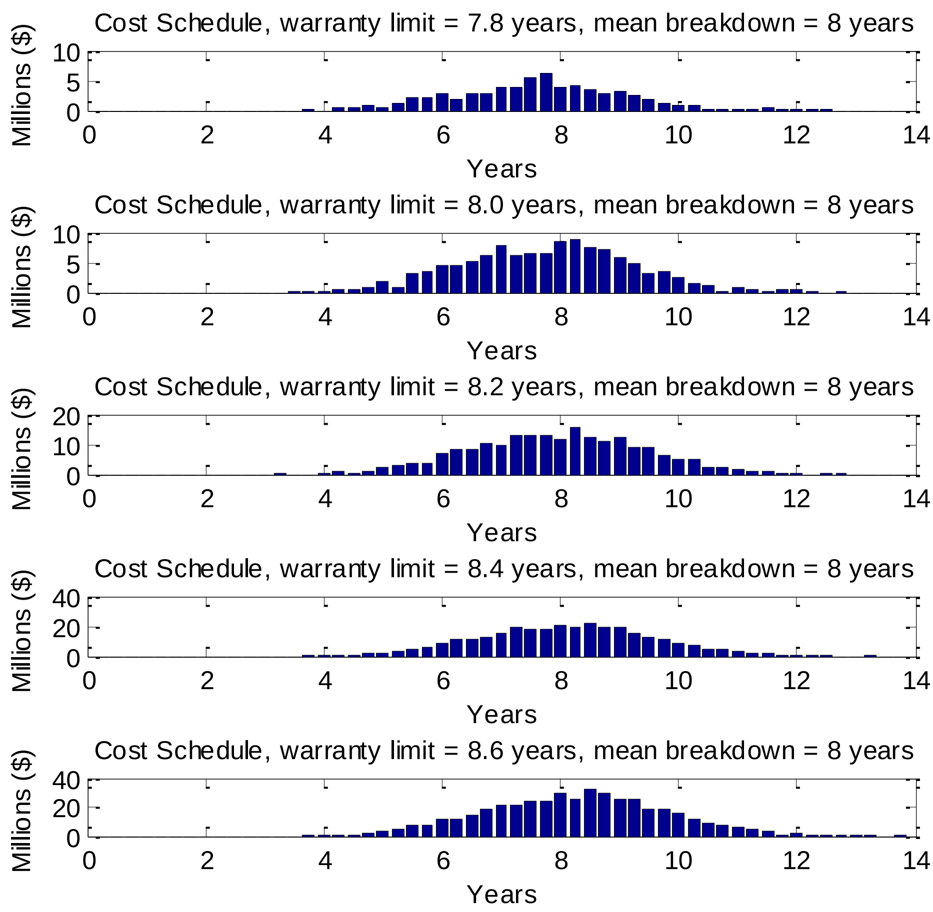


Figure 3-15. Cost Schedule, constant reliability function, and warranty limit change in small increments.

Keeping warranty limit constant and changing reliability function also has the similar effect. The plots are shown in Figure 3-16. It also can be seen that the replacement cost is predominant in both Figure 3-14 and Figure 3-16. In fact, more than 90% of the costs are incurred by battery replacement.

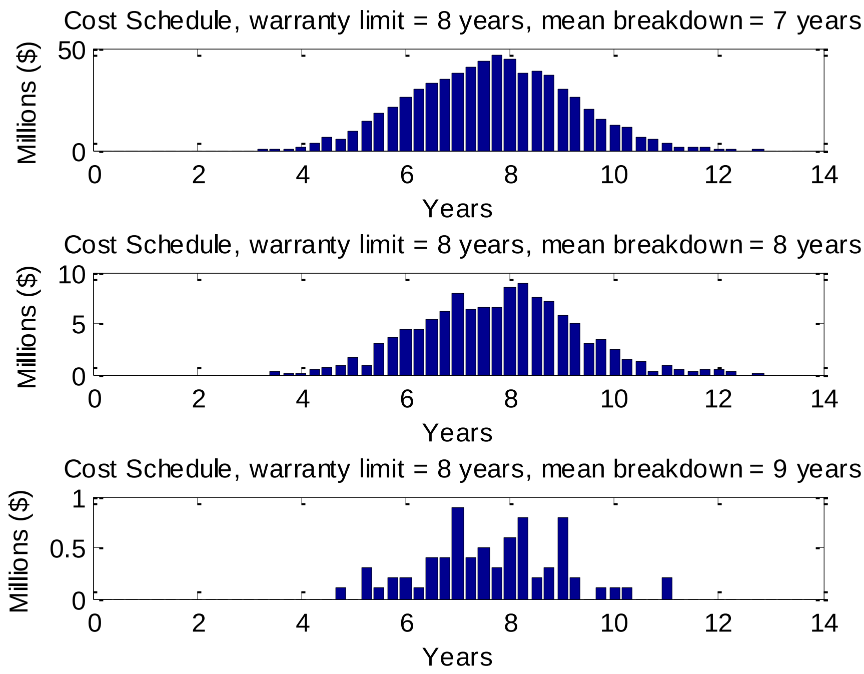


Figure 3-16. Cost schedule when warranty is constant, altering reliability function.

3.3.4 **Effects of Altering Costs**

When the IR, MR and replacement costs are changed, there is no effect on the number of repairs/replaces. However, it can be viewed as putting different weights on different types of repairs/replaces. That is, they can change the significance of different types of repairs. Although it is not popular in literature, when a component fails within an automotive system, it is more likely to be replaced rather than repaired when in the earlier period of warranty. Thus, it is an important decision factor when design warranty and battery reliability. However, due to the setup of the simulation, predominant costs are from battery replacement. Changing costs in minimal repair and imperfect repairs essentially have only limited effect on both C_{SC} and C_{SM}, and additionally the aggregated cost schedule.

3.3.5 **Effects of Purchasing Time Function (Sales Prediction)**

To understand how the prediction of sales as an input to the model affect the life cycle costs, the results based on the Bass fusion function can be compared with two alternative distributions: uniform distribution and an arbitrary triangle distribution. As shown in Figure 3-17, it turns out that altering purchase time function has virtually no effect on different cost types. This is due to the fact that when combining sales distribution with breakdown function, it is essentially taking the convolution of these two functions. Any high frequency information such as the shape of the distribution is lost after the convolution (Liang, Jin, & Ni, 2014). Because of this, a less-accurate prediction of sales may still result in an accurate prediction of cost schedule as long as the total number of customers and how many years it plans to sell are correct. Note that for all three sales distributions, the majority of the batteries are bought within 3 years.

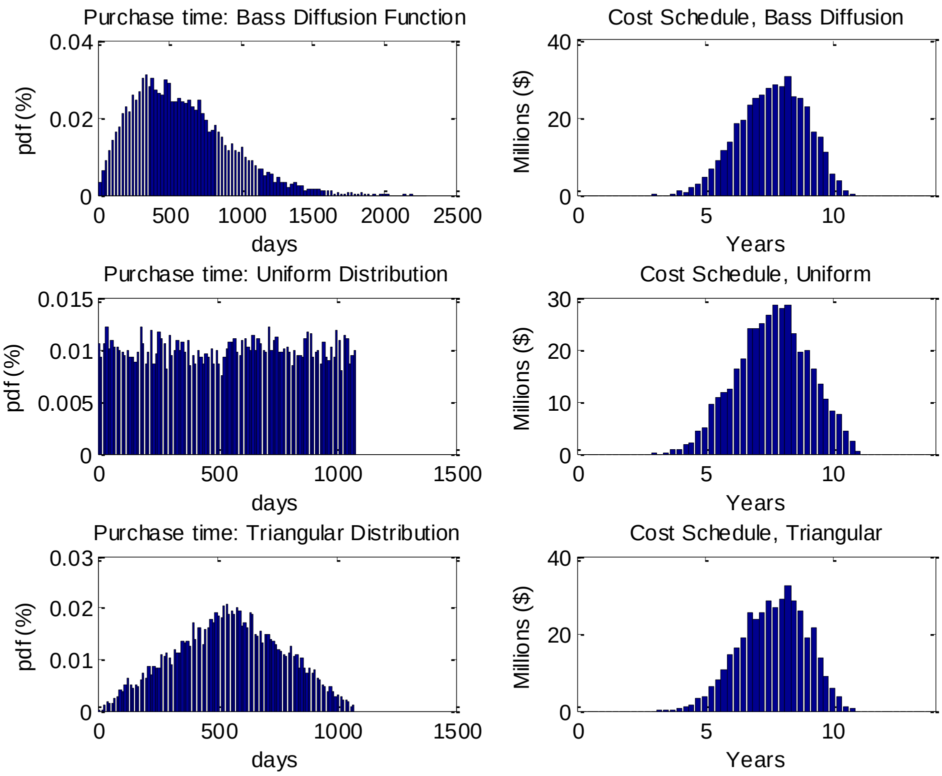


Figure 3-17. Changing in Sales distribution results virtually no change in costs.

3.4 Conclusions

This chapter investigates the methods for estimating lifecycle warranty cost for EV batteries with a two-dimensional warranty model. This research attempts to shift the traditional view of warranty from a simple production protection and marketing tool to a more intimate link between customers and manufacturers. This also builds a foundation for future automotive business model development. Effects of altering influence factors, such as life expectancy (reliability), sales, and return behavior, are also studied. For battery reliability, an AFT model is used to extrapolate the base reliability function to drivers with different usage rates. Three types of failures are modeled to cover various failure modes of EV batteries – Replacement for entire pack, minimal repair and imperfect repair. Simulation models are developed to estimate the warranty-related aggregated costs for customers and manufacturers respectively. From a numerical study on the effects of various influencing factors, it is found that customers, who have limited knowledge about the true battery life, have greater incentives to choose battery with long warranty because they try to minimize the risks of paying repair costs after warranty expires. However, EV manufacturers prefer to select a warranty limit similar to the mean breakdown time. Therefore, there exists a tradeoff between the customer's incentive and manufacturer's incentives for the optimal decision on warranty limit. The methods for warranty cost estimation provide a useful tool for manufacturers to design their warranty scheme, and the results additionally provide some guidelines for the directions of technology improvement to further reduce the warranty costs to both sides.

CHAPTER 4

Remanufacturing Supply and Demand Matching For EV Battery Packs

4.1 Introduction

The first EV introduced to the United States, the Honda Insight, appeared in 1999. Even with numerous governmental incentives for consumers to purchase an EV since then, the market share of EV cars is currently only about 1% of the total car sales in the US. One major factor is that both the initial cost and the life-cycle cost of an EV are significantly higher than that of normal internal combustion engine (ICE) vehicles. Battery packs are the main contributor for this high cost. It is estimated that it costs Tesla \$195 per kWh and GM \$215 kWh to produce their battery packs in 2016 (InsideEVs, 2016). Moreover, the product lifecycle cost, or the cost to own an EV during its entire life is also dramatically higher compared to ICE vehicles. This is due to the shorter lifespan of the battery packs compared to that of the vehicle itself. Battery packs in current generation EVs can only last 5 to 7 years under the engineering specifications for vehicle power batteries. However, the average ownership of passenger vehicles is around 12 years. This means a battery pack needs to be replaced during the lifetime of a car.

Currently, this is not an issue because the majority of the EV batteries have not reached their end-of-life. In addition, to attract more customers, EV manufacturers (OEMs) usually provide a liberal warranty, even at a loss. In many cases, battery warranty period is sufficiency long such that if the old battery degrades, a replacement battery is provided by the OEM at the OEM's expense.. At present, because of marketing reasons and generous investors' support, this is implementable. However, this is not sustainable and cannot be a long-term strategy simply because many EV OEMs are operating at loss.

Furthermore, battery technology cannot keep up with the industry. Even though some manufacturers, such as Tesla, claim that battery cell's price can go to $100 per kWh by 2025 (GreenTechMedia, 2016), the battery pack for a Tesla Model S will still cost more than $15,000 to produce, if other related electronics are included. On the other hand, a brand-new low trim Honda Civic, a very popular small size sedan, only costs $16,000. So, OEMs are desperately trying to lower the battery cost and cannot entirely reply on technology improvements.

One way to solve this problem is to remanufacture the battery packs. It is estimated that remanufacturing an EV battery costs 20% of the original cost (Jin et al., 2013), and remanufactured batteries can be used as battery replacement after the first battery retires. The intuition is very straightforward: if battery warranty is eight years and the battery fails during the seventh year, the manufacturer only needs to replace a battery that last for one year or longer. A new battery that can last seven or eight years is excessive. Moreover, if a battery dies during the ninth year and the customer only wants to use the car for 12 years, this customer can buy a battery replacement that can last for three years. He/she most likely does not want to spend another $15,000 ~ $20,000 for a new battery replacement.

To implement this business model successfully, a better understanding of the interaction between the customer and OEMs during the entire car lifecycle is required. The goal of this chapter is to demonstrate a way to characterize the relationship between the customer and OEM, and to determine the feasibility of a remanufacturing business model. Additionally, an optimal solution is determined for the model.

This chapter is organized as the following: Section 4.2 gives an overview of EV battery pack remanufacturing operation. Section 4.3 illustrates what factors can influence remanufacturing supply side and how they are influenced. Similarly, Section 4.4 demonstrates demand side behavior. In Section 4.5, different demand-supply matching mechanisms are evaluated, and an optimal solution is provided at the end. Conclusion and future direction is stated in the final conclusion section.

4.2 Remanufacturing

Remanufacturing may have different meanings in different industries. In this research, it is the process to reconstruct a product to certain specifications from field returned used products and/or newly manufactured components. One aspect that is different from other industries is that the final remanufactured product may contain newly produced components.

Although remanufacturing has been studied and implemented for decades, one of its fundamental challenges, namely matching supply side and demand side fluctuations and uncertainties, is still largely untouched. For traditional manufacturing, only demand side (customer side) has large fluctuations. Through different supply chain regulations, supply side fluctuations can be viewed as controllable and predictable. On the other hand, remanufacturing supply relies on customer returns, and it is highly uncontrollable and unpredictable. This is one of the main reasons why remanufacturing only flourishes in a handful of industries, where both demand and supply are highly predictable or "buffers" can easily be placed. Here, buffers can take many forms, such as the high profit margin in medical devices, aerospace or large machinery industries. Because profit margin is high, it is still profitable after a 30% to 40% fluctuation. Other buffers, such as inventory, are also commonly used. Besides buffers, other mechanisms, such as contracts, are often used to regulate supply-demand uncertainties. For example, many printer OEMs sign contracts with their large customers and guarantee the cartridge and toner usage for certain period. During this time period, the return and supply of cartridge and toner replacements can be regulated by the printer OEMs. Essentially, it creates a "closed loop" between OEMs and customers.

The key of this research is to reduce both the demand side and supply side fluctuations and uncertainty by creating a similar "closed loop" between EV OEMs and customers. To establish this loop, the traditional one-time contact relationship (car purchasing) needs to be extended to a lifelong relationship. Luckily, modern EV OEMs, such as Tesla, also operate their own repair centers and charge stations (gas station equivalent), and car warranties can be used similar to the printer cartridge/toner contracts. By implementing more effective warranty and repair/remanufacturing policies, OEMs can better forecast customers' behavior and have a more predictable and controllable remanufacturing system.

For this research, discrete event simulation (DES) is used to model different scenarios. DES models systems as a sequence of events and/or states. Each one of them occurs at a particular time and is affected by other events and/or states. Here, events can be human actions, such as EV purchasing, deciding which battery module to remanufacture, or a mechanical module, such as degradation and break down of battery packs. Pure analytical model is not implemented due to the complicated interconnections between events.

4.3 Supply Side

4.3.1 **Overview**

Supply side is where customers supply used battery packs so remanufacturers can transform them into remanufactured ones. For this research, only failed and returned batteries are considered. Certain end-of-Life (EOL) scenarios, such as batteries from discarded cars due to their old-age or replaced by newly purchased cars, are not considered because they are difficult for remanufacturers to collect. That is, the main source of returned batteries comes from repair centers. It is also assumed that those repair centers and remanufacturing centers are operated by EV OEMs, thereby enabling OEMs to coordinate their inventories and actions. For example,, Tesla owns all its repairing centers and remanufacturing centers. Since Tesla did not open its diagnosis tools and internal protocols to public, it is very difficult or impossible for third party repair shops to diagnose and repair Tesla's battery packs. It is also true for the Nissan Leaf, Chevy Volt and most other EV models. One reason is that the detailed battery control scheme is still a closely guarded trade secret and EV makers' competitive advantage.

Compared to the supply side of traditional manufacturing, remanufacturing supply varies greatly in the returned parts' quality, quantity and return time. One of the aims of this chapter is to characterize this variation, learn its effects, and determine ways to reduce its effects.

4.3.2 **Supply Variation Influential Factors**

Some influential factors are borrowed directly from previous chapters. Sales estimation is represented by the same Bass Diffusion model from Chapter 2 and 3. Usage rate is also the same Gamma distribution from previous chapter. For warranty, the standard two dimensional non-renewing free replace/repair warranty with effective warranty and scaled by the usage rate is also the same as previous chapter. New influential factors are added as the following.

4.3.2.1 Vehicle End-of-Use Date

Vehicle end-of-use date is considered because during simulation, sometimes the expected end-of-use date takes place before first battery break down or warranty expiration. According to CNBC (CNBC, 2015), the average length of a car life in the United States is currently around 12 years. Some cars can be used as high as 20 years, and some others only used for 5 to 6 years. For simplicity, a truncated normal distribution is used to simulate expected car life. Truncated normal distribution has many normal distribution properties, yet it has a finite support.

$$
\begin{aligned}
&pdf(t) = \frac{\phi(\frac{t-\mu}{\sigma})}{\sigma(\Phi(\frac{b-\mu}{\sigma}) - \Phi(\frac{a-\mu}{\sigma}))} \\
&\text{where} \\
&\phi(\xi) = \frac{1}{\sqrt{2\pi}}\exp(-\frac{1}{2}\xi^2), \quad \text{and} \\
&\Phi(\xi) = \frac{1}{2}(1 + erf(\frac{\xi}{\sqrt{2}}))
\end{aligned}
\tag{4-1}
$$

Here, the mean of the distribution is $\mu = 144$ months or 12 years, standard deviation $\sigma = 24$ months or 2 years. It is truncated at $a = 6$ months and $b = 240$ months or 20 years. The shape of the distribution is illustrated in Figure 4-1

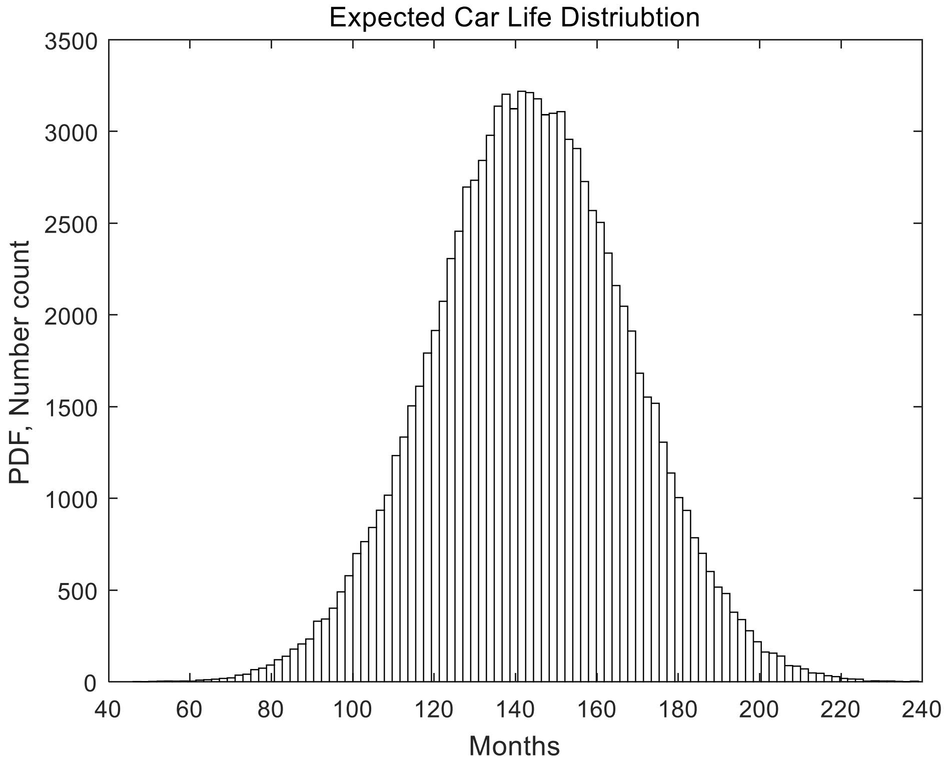


Figure 4-1. Car life distribution.

4.3.2.2 Battery Reliability, Degradation Process and Failures

For this research, four types of failures are considered: electronic components, frame/enclosure, battery cell physical and battery cell degradation failures. Like many complex systems, Li-ion battery packs are built into a hierarchical structure. The pack is made of a number of battery modules interconnected by an electronic power/communication network and controlled by a battery management system (BMS). Each module, in turn, consists of a number of battery cells interconnected by a module level network and controlled by a module controller. For this research, the remanufacturing process in consideration disassembles modules from an old pack and remanufactures it into a new pack. The disassembly on battery cell level is not considered here.

For electronic components failures, BMSs, module controllers, electronic power/communication network at different levels, and different sensors (voltage, current, temperature, vibration sensors at different levels) failures are included. Frame/enclosure failures usually are comprised of punctures and breakages of different kind, different leakages, and other physical damages to the battery frame or enclosure. Battery cell physical failures include physical damages at the cell level, such as broken connections, internal shorts, and internal opens. These failures are often caused by driving conditions, such as physical vibration, extreme temperature change, metal fatigue and so on. For these three types of failures, when a component has truly failed, it is discarded. There is no remanufacturing or reuse of this component anymore, because it is cheaper to replace a new one than to remanufacture an old one. Finally, battery cells can age and degrade, thereby producing a gradual decrease in capacity. Failure status is reached when a battery degrades to certain threshold, such as 70% of its original capacity.

For this research, electronic components are all grouped together and their failures are represented by a Weibull distribution. All physical module failures are grouped together and represented by another Weibull distribution. Similarly, frame/enclosure failures are also modeled according to Weibull distribution. Weibull distribution is commonly used for both electronics and mechanical failures (Rinne, 2008). The reason these three failure types are separated and not grouped as one is because their diagnosis processes are different and treated differently during repair that will be explained in detail in the repair type section. A Weibull distribution has the form of:

$$pdf(t) = \begin{cases} \frac{k}{\lambda}(\frac{t}{\lambda})^{k-1}\exp(-(t/\lambda)^k), & t \geq 0 \\ 0, & otherwise \end{cases}, \tag{4-2}$$

where $k > 0$ is the shape parameter and $\lambda > 0$ is the scale parameter or the so called "failure rate" of the Weibull distribution.

For the simulation, it is assumed that there are 10 modules in a battery pack. If one fails, the entire pack needs to be repaired. Likewise, any component fails, it is sent to a repair center for diagnosis. For electronics, the shape parameter k is assumed to be 5, and $\lambda = 1/(30 \times 12) = 1/360$. For frame/enclosure, $k = 4$ and $\lambda = 1/(25 \times 12) = 1/300$. For module physical failures, $k = 4$ and $\lambda = 1/(30 \times 12) = 1/360$. Thus, all the electronics related components have failure rate of one per 30 years or 360 months, and mechanical parts have failure rate of one per 25 years or 300 months. The shape parameter k determines the standard deviation or how the distribution will spread. Moreover, because there are 10 modules, all 10 module failures are simulated and the pack failure depends on the first module failure. If the rest of modules are used in remanufactured packs, their distribution will not be reset. That is, from simulation's perspective, a module's physical failure date is set when the module object is created in simulation. The distributions are shown in Figure 4-2

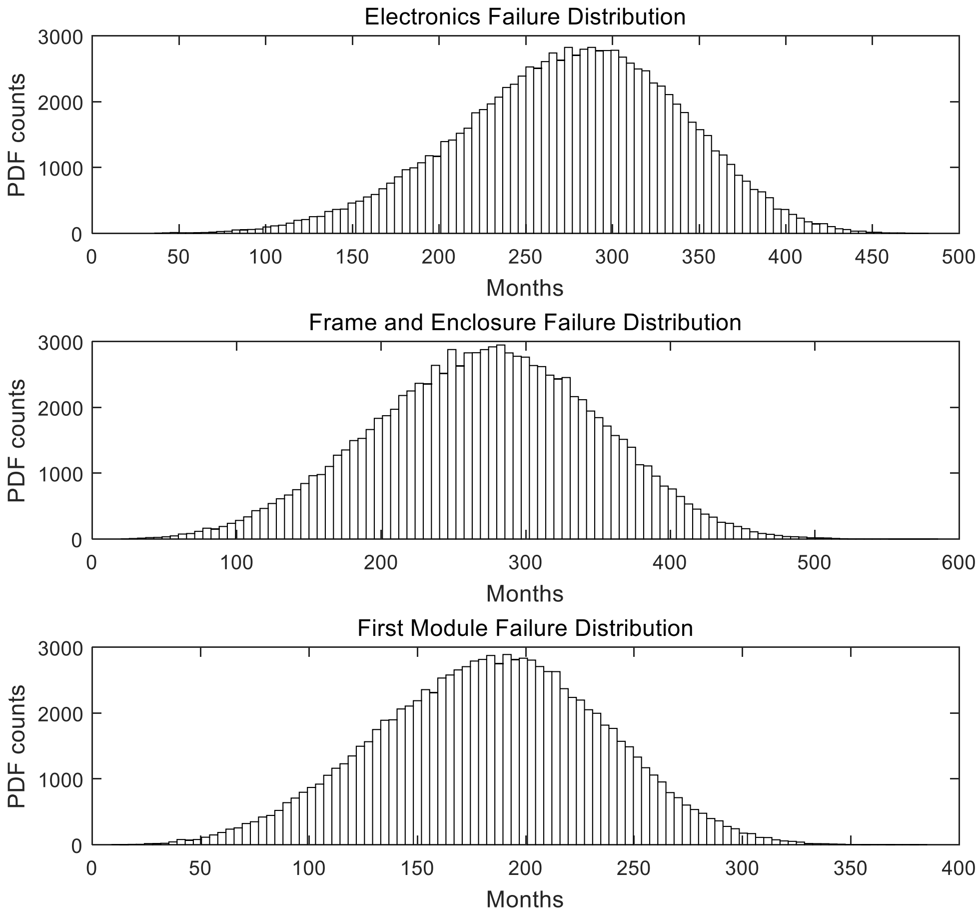


Figure 4-2. Distributions for pack electronics, frame/enclosure and module physical failures.

4.3.2.3 Battery Degradation Process and Related Failures

GM wrote in its newest 2016 Chevy Bolt's Manual on page 322 that "Depending on use, the battery may degrade as little as 10% to as much as 40% of capacity over the warranty period." (Trek, 2016) Its warranty period is standard 8 years or 100,000 miles. For other EV OEMs, such as Tesla, degradation is excluded from their warranty completely. From the "fine print" of its warranty on its official website, Tesla states:

> *"The Battery, like all lithium-ion batteries, will experience gradual energy or power loss with time and use. Loss of Battery energy or power over time or due to or resulting from Battery usage, is NOT covered under this Battery Limited Warranty."*

Both quotes clearly illustrate that battery capacity degradation is a serious issue in EV industry.

The Li-ion battery aging mechanism has been studied extensively in the past decade. Many efforts have been devoted to physics-based model including electrochemical model, equivalent circuit model, etc. However, data driven methods such as reliability function or statistical failure behavior are generally unknown because it requires a large number of run-to-fail battery test data. Unfortunately, most of the degradation data for commercial EV battery packs are confidential to EV OEMs. Reliability functions generally are inference from either known degradation processes or real measured condition metrics, such as crack size, loss of efficiency and other factors. In this research, the degradation processes of the Li-ion battery can be modeled using existing techniques, such as first hitting threshold time (FHTT), to transfer the physics-of-failures (PoF) to reliability functions (Letot & Dehombreux, 2009; Lee & Whitmore, 2006; Van Noortwijk et al., 2005). Once a base reliability function is developed for average drivers with an average usage rate, an Accelerated Failure Time (AFT) model is used to extrapolate the base reliability function to drivers with different usage rates. It is also assumed that the degradation process is only influenced by time and usage. Other causes, such as operating temperature, state of charge for each cycle, charge protocols, and driving patterns, are not considered in this research.

If τ is a random variable representing failure time, the reliability function and its complementary, failure functions, are the same as equations (3-10) to (3-13). Different parameters of these equations are obtained using equations (3-8) and (3-9).

As discussed in Chapter 3, reliability function can be affected by usage rate. Accelerated Failure Time model is used to scale reliability function in the time domain. The scaling process and the parameters used are the same as equations (3-14) to (3-16).

4.3.2.4 Combine Failure Types

After a customer purchases an EV, the first failure is the first occurrence of the combination of all four failure types. Subsequent failures are more difficult to determine analytically because it depends on how the first failure is repaired and if a remanufactured battery pack is used as replacement. The distribution of the first failure is shown in Figure 4-3. Notice that almost half of the failures will take place before the warranty expiration date (eight years or 96 months). However, after taking effective warranty into account, the number of failures is much smaller (not shown in graph) because both the warranty and degradation process need to take usage rate into account. Even with considering this factor, a change in failure type composition can be seen in Table 4-1, which is generated by the DES simulation.

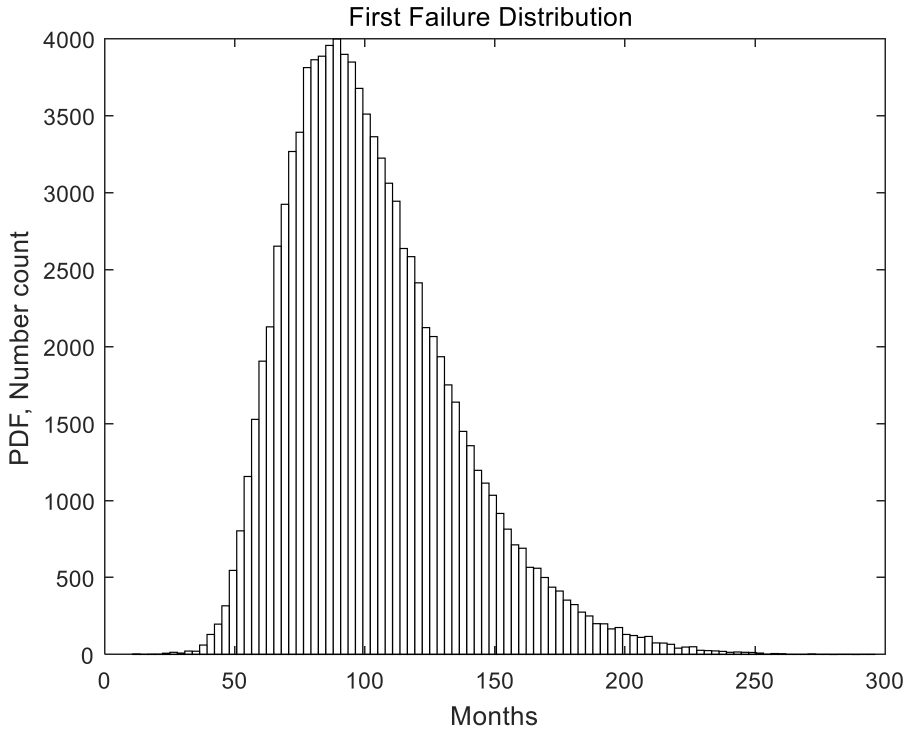


Figure 4-3. First failure date.

Table 4-1. Simulated failure type composition before and after warranty period.

Failure types	% before warranty expiring	% after
Electronics	18	24
Frame/enclosure	15	27
Module physical related	20	22
Module degradation related	47	27

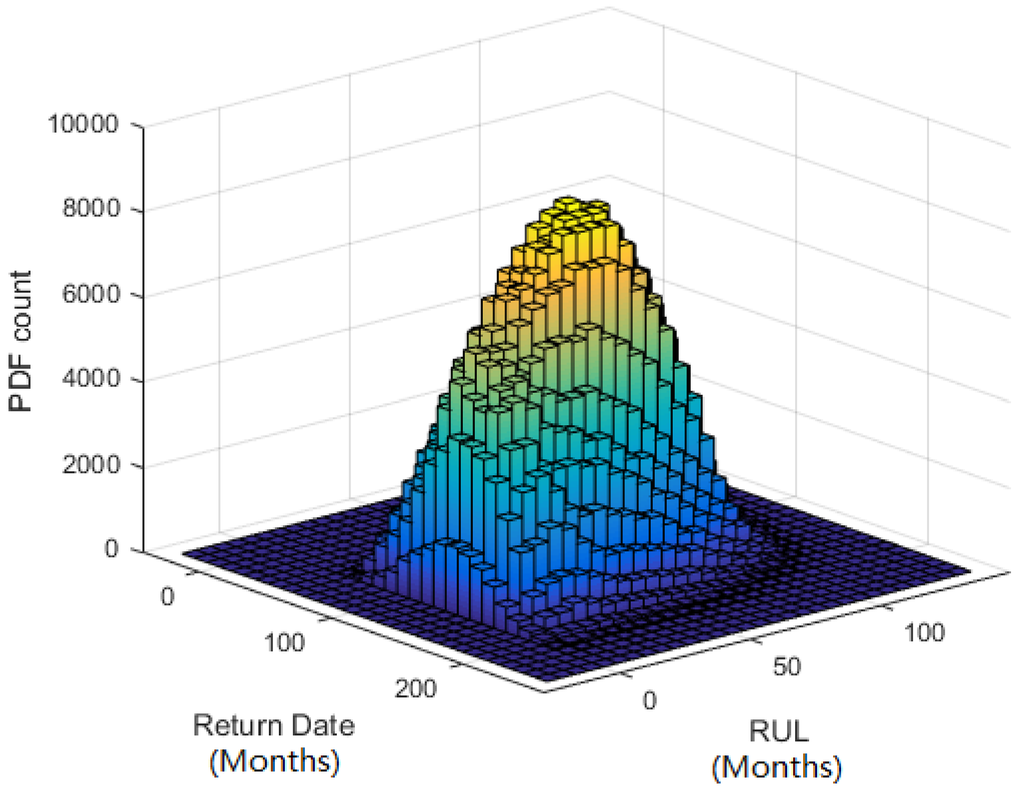
4.3.3 **Remaining Useful Life (RUL)**

Remaining Useful Life (RUL) of a module is the key parameter to determine if a module still can be used for remanufacturing. There are several methods to express the RUL of a battery, such as remaining capacity. For a more consistent comparison, and simpler calculation, estimated remaining useable time is used for this research. For example, if a battery module is simulated to last for 10 years or 120 months, and the usage rate is 40 miles/day, the module failure date due to degradation is changed to: 120 months / 40 miles/day * 35 mils/day = 105 months. If the battery pack is returned due to electronics failure at year eight or 96th month, the RUL is (105 months – 96 months) * 40 miles/day / 35 miles/day = 10.3 months. RUL needs to be scaled back, so different modules can compare with each other.

4.3.4 **Supply During Market Lifetime**

Market lifetime is defined from the time the first product is sold to the time the last product is discarded by its user. A sample run is illustrated in Figure 4-4, and the simplest remanufacturing condition is used for this plot. Namely, all replaced batteries are remanufactured, and inventory is infinite. Battery modules are also used based on the principle of closest capacity to match. The conditions will be explained in detail in the matching section. In Figure 4-4, the date axis displays when a remanufacturable module is returned to the remanufacturing center, and the RUL axis shows the quality. The return date ranges from around the second year

(24th month) all the way to 16th year (200th month), and RUL ranges from one month to about 10 years (120 months). Return date is much longer than the lifespan of a battery, mainly because the car purchase date is added. It is also due to the usage rate scaling. It is evident that return date peaks when return date is 90 months and RUL is 70 months. The electronics, frame/enclosure failures are the main contributor for the peak. This is different from Table 4-1 because subsequent failures and remanufactured battery pack failure are also considered here. Table 4-1 only considers the first failure for new battery packs.



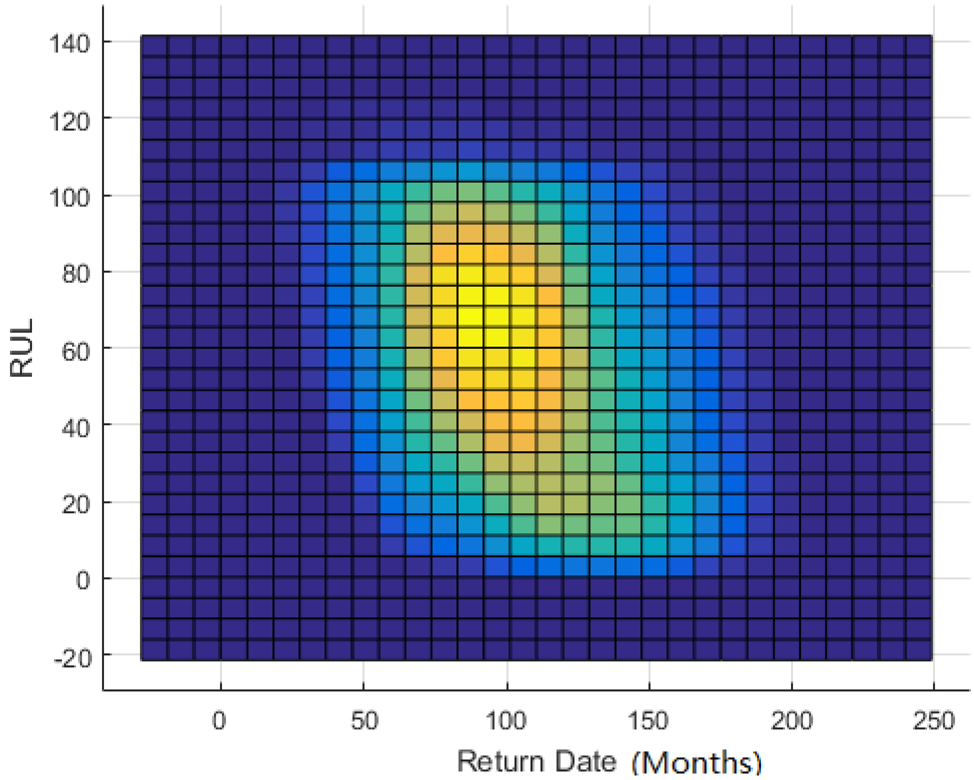


Figure 4-4. Supply during market life (3D view and top view).

4.3.5 **Major Assumptions for the Supply Side**

There are several major assumptions for the supply side. Namely,

- All the distributions are independent from each other. All the interactions between them are not considered, such as earlier product may have lower reliability than later product.
- No second-hand ownership is considered. That is, no warranty, usage rate or degradation changes.
- Usage rate is constant, and no events outside the four types of failures are considered, such as accidents.

- Battery degradation rate is constant for each module throughout the life-time of the module unless it is remanufactured into another battery pack. The degrading rates are different for different modules in the same pack.
- Assume a linear degradation, and failures follow Weibull distribution.
- 100% diagnosis accuracy. All the failures can be diagnosed exactly, and degradation rate is also known.
- 100% repairing/remanufacturing rate. There is no repair or remanufacturing loss.
- No transportation, diagnosis or repairing/remanufacturing time. Because the time unit for this research is month, and the transportation and remanufacturing time usually are one or two weeks which is much less than the time scale here. This also implies that there is no geographic barrier, all the inventory around the world can act as one.
- Failures are 100% detectable by customer. When customers see a warning indicator on dashboard, they send their car to repair center without delaying.
- No third-party involved. EV companies, such as Tesla, do not sell spare parts and diagnosis tools to third party and do not provide specs for the diagnosis codes.

4.4 Demand Side

4.4.1 **Overview**

Unlike traditional demand, remanufacturing demand is defined by four factors: time, price, quantity and quality (RUL). It characterizes how many of a remanufactured product is wanted by customer at each time interval, each price level and each quality level. Because there is only one supplier of the remanufactured batteries, price is fixed. Hence, only the other three factors are considered.

4.4.2 **Two Types of Demands**

Two types of demands are separated into the time dimension by warranty expiration date. Before this date, demand is from the OEM/remanufacturer because the product is paid by the OEM directly. The OEM additionally decides the quality of the product. To minimize the cost of battery replacement, the lowest suitable quality remanufactured battery is supplied to the customer. For this research, a half-year "safeguard" is added. For example, if warranty is eight years, and the battery pack is failed at year six with usage rate of 40 miles/day, a RUL of (2 year + 0.5 year)/35 miles/day * 40 miles/day = 2.86 years remanufactured pack is supplied. For the simulation, the cost is additionally added to the OEM.

After the warranty, customers decide the demand. Two types of battery can be chosen from: brand new and remanufactured. Here, the RUL for remanufactured units is calculated as the difference between expected car end-of-use date and return time plus a safeguard of half year, and usage rate is also applied as before. For the simulation, it is assumed that 80% of customers will purchase a remanufactured battery, 20% new, chosen at random. The cost is added to customer.

4.4.3 **Failure Types and Demanded Parts**

As stated in Section 4.3.2.2, there are four types of failures. Each type of failure will demand different type of parts and the reliability function will be set or reset differently. Generally speaking, when a battery pack is sent to a repair center, both failure and module degradation condition is checked. If a failure is found, the related part will be replaced. At the same time, if a module cannot last until the end of the warranty period, it is also replaced. It is repair center's goal to ensure no more failure or degradation will take place before warranty ends. After warranty period, because it is not EV OEM's responsibility to ensure the condition of the battery, repair centers only check for failures. The repairing/replacement policy for simulation is summarized in Table 4-2.

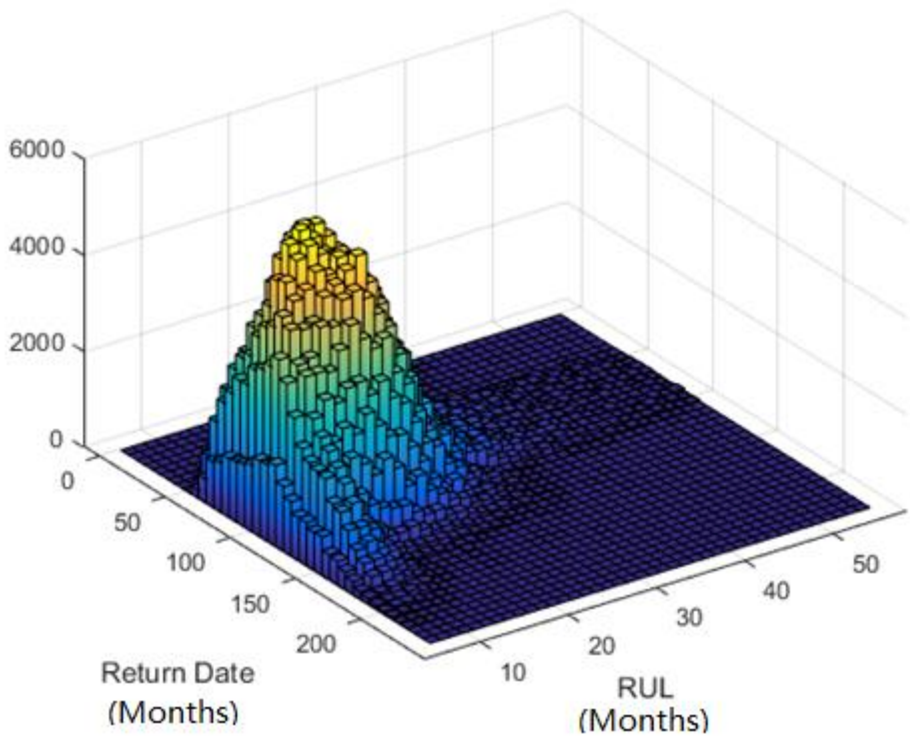
Table 4-2. Parts replacement and remanufacturing policy.

Warranty Expiration	**Failure Types**	**Failed Part**	**Modules**
Before	Electronics	Replace with new, reset part reliability function to new	Check if other modules can last till warranty expiration. If not, replace with remanufactured having right RUL. If cannot find, use higher RUL; still cannot find, use new parts. Set reliability function according to condition.
	Frame/enclosure	Replace with new,	Check if other modules can last

		reset part reliability function to new	till warranty expiration. If not, replace with remanufactured with right RUL. If cannot find, use higher RUL; still cannot find, use new parts. Set reliability function according to condition.
	Module physical	Replace with remanufactured, set reliability function according to condition	Check if other modules can last till warranty expiration. If not, replace with remanufactured with right RUL. If cannot find, use higher RUL; still cannot find, use new parts. Set reliability function according to condition.
	Module degraded	Replace with remanufactured, set reliability function according to condition	Check if other modules can last till warranty expiration. If not, replace with remanufactured with right RUL. If cannot find, use higher RUL; still cannot find, use new parts. Set reliability function according to condition.
After	Electronics	Replace with new, reset part reliability function to new, or replace entire pack new	Do nothing
	Frame/enclosure	Replace with new, reset part reliability function to new, or replace entire pack new	Do nothing
	Module physical	Replace part with remanufactured, or replace entire pack new	Do nothing
	Module degraded	Replace part with remanufactured, or replace entire pack new	If not replaced with new pack, check other modules can last as long. If not, customer pay to replace

4.4.4 **Demand during Market Lifetime**

Unlike the supply side, which is determined mainly by the natural degradation process and failures, demand during market lifetime is mainly determined by how a battery is diagnosed, repaired and replaced, and other human factors. It can be seen from Figure 4-5 that the demand peaks when return date is approximately 95 months and RUL is 14 months. Note that the RUL axis starts from the sixth month. This is because six months of safeguard is added for all remanufactured packs, as stated in section 4.4.2.



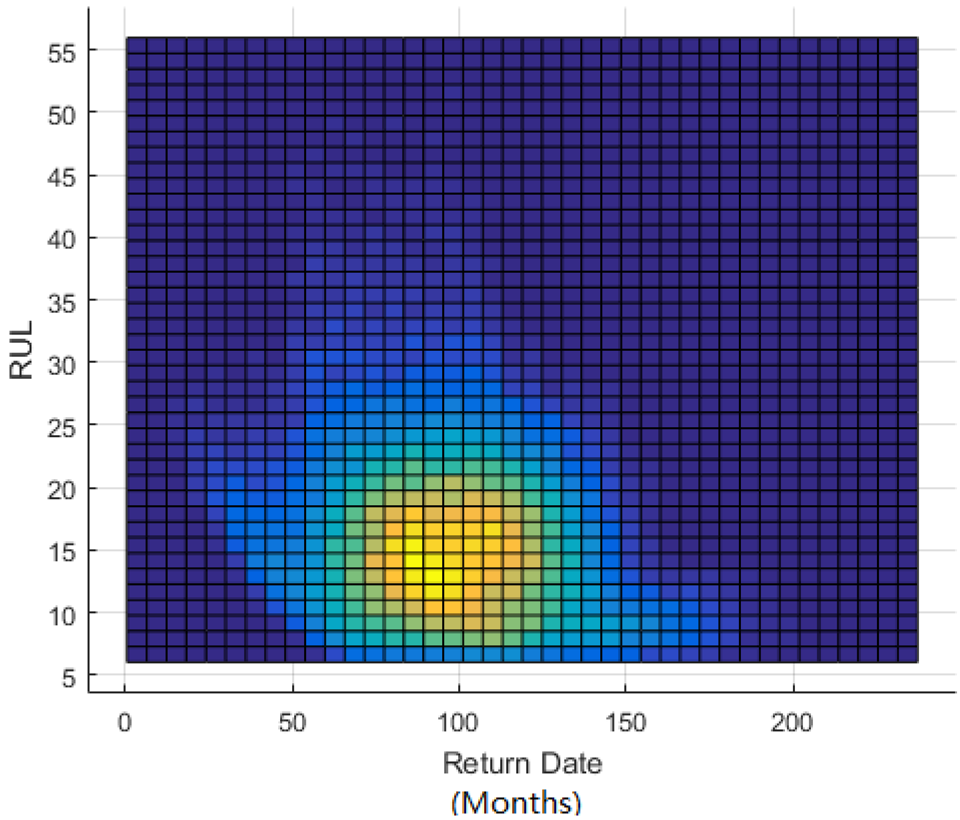


Figure 4-5. Demand during market lifetime (3D and top view). Both Return Date and RUL are in months.

4.4.5 **Major Assumptions for the Demand Side**

There are a number of assumptions for the demand side:

- Consumers behave rationally and their behavior is predictable. For example, they will retire their EV only if the expected end-of-life time is reached.
- Consumer behavior will not be changed by outside factors. For example, if an EV fails 3 or 4 times, they still keep it and drive it as before.

No geographic consideration is included. Customers from all over the world will behave the same.

- Repair center knows all about drivers, such as usage rate (total driven distance divided by time).
- Inventory cost is neglected.

4.5 Demand and Supply Matching

4.5.1 **Overview**

The goal of the matching process is to shift both supply and demand (Figure 4-4 and Figure 4-5) simultaneously such that the overlap between them can be maximized. A number of "shifting enablers" are considered. However, each one of them can only change certain aspects of supply or demand curves. By combining them together, the best optimization may be achieved.

For this research, the total cost for manufacturer is used as the objective function in the optimization. The following cost assumptions are additionally made: For a new battery pack, electronics costs $500 and frame and enclosure cost $1000, and a single module costs $2000. Thus, a brand-new pack costs $21,500 in total. For repairing and remanufacturing, transportation fee from repairing center to remanufacturing center is $200 per pack, diagnosis fee is $200, repairing is $100, and remanufacturing is $100 per module. Labor costs are included in these fees. For inventory, the cost is $5/module/month. It is assumed that there is no inventory cost for other non-module or non-pack items. For a simple scenario, a battery pack fails before the warranty expiration date. After diagnosis, a battery management system

(BMS) is replaced, and 2 modules are also replaced by remanufactured ones because they cannot last till warranty expiration date. The BMS is replaced at repairing center and 2 modules are replaced at remanufacturing center since modules are stored at remanufacturing centers. The total cost is $200 diagnosis cost + $200 transportation cost + $100 repairing cost + $500 new electronics (BMS) cost + $100 x 2 module remanufacturing cost = $1200 + inventory cost for the 2 modules.

4.5.2 **Repairing/Remanufacturing Policies**

Four repairing policies are considered for analysis. The first is to replace all failed parts with new packs. This was performed on some EV models during their early dates since no repairing or remanufacturing facility was built, and it was more economical to provide a new pack than spend manpower to diagnose and repair. The second policy is to replace all failed components with new components. The third one is to replace failed modules with remanufactured modules. The detail of this policy is stated in Table 4-2. The fourth policy is to use remanufactured replacement according to current inventory. For example, if a module with RUL of 1.5 years is demanded, but most common RUL in inventory is three years at this moment, then module that has RUL of three years is used. However, if demand RUL is greater than most common RUL inventory, demand RUL is used. The purpose for the fourth policy is to lower the inventory cost, and to extend battery life by supplying better modules.

The result is shown in Table 4-3. Four columns of the table correspond to the four repairing and remanufacturing policies. The first 11 rows show the break down by event sequences. The letters are coded as: B = breakdown, W = end of the warranty, and C = end of car life. For example, CW means there is no failure, and end of car life happens before warranty ends, and BBWBC means a battery breaks twice before warranty and breaks once between warranty ends and end of the car life. This helps both debugging the DES simulation during development and having an overall picture of when and why batteries may fail after the simulation is done. Percent supply used is the total percentage of supply being used during the entire market time. It can be seen that without optimization only around half of supply is used. Similarly, demand is also not entirely met. OEM average cost is mainly the cost OEMs spend on warranty. Average customer cost is the cost after the warranty. The sum of these two are the total cost needed for the entire lifecycle. OEM total cost is the total cost OEM needs to spend on all of the batteries during the entire market life. It can be shown in Table 4-3 that, although no matching/optimization is done, the costs for both customer and OEM are decreased significantly. This decrease is due to the cost of remanufactured parts being significantly lower than brand new parts.

Table 4-3. Failure and cost break down during market life by remanufacturing policy types.

	New pack	**New Part**	**Reman., RUL**	**Reman., inventory**
CW (count)	5009	4966	5015	5020
BCW (count)	10046	9041	7032	8067
BBCW (count)	5092	5924	8018	7021
WC (count)	9951	9012	9011	8958

BWC (count)	30922	11001	11903	13071
BBWC (count)	6981	17933	15060	12992
BBWBC (count)	1041	6029	8958	7938
BWBC (count)	8057	10091	10021	9003
BWBBC (count)	947	7096	7988	7096
WBC (count)	20962	11045	7955	11097
WBBC (count)	1018	7915	8954	9985
Percent supply used (%)	0	0	47.90%	56.45%
Percent demand satisfied (%)	0	0	58.24%	64.29%
OEM average cost ($)	15783.39	8954.42	6129.25	5858.77
Customer average cost ($)	9137.90	9689.26	6724.87	6645.39
OEM + cust. average cost ($)	24921.29	18643.68	12854.12	12504.16
OEM total cost ($B)	1.58	0.90	0.61	0.59

4.5.3 **Warranty Policies**

Changing warranty policies is always a complicated marketing decision because it may potentially change the market share significantly. Therefore, the traditional terms, such as time and miles driven are not changed here. A new dimension, charging cycle, is added. As stated in the warranty section, the battery failure due to degradation currently is not included in warranty for many EV makers. Here, charging cycles only affect capacity degradation, and the hope is that the market behavior will not be altered.

It is concluded that Li-ion battery degradation depends on its charging and discharging cycles (Zhang, 2006). Charging/discharging cycle dependent warranty currently exists in many industries where Li-ion batteries are used. It is very common in electric power tools and machineries. Milwaukee tools' warranty guarantees 5 years or 2000 charging cycles (Tools, 2016). It is also common in consumer electronics, such as HP laptops and Apple computers. Golf carts, such as

EzGo, also offer similar warranties.

There are several ways to calculate the charging cycles. Apple laptops, such as MacBook and MacBook Pro use simple sum of all charging. For example, today it is charged 30%, from 70% to 100%, and tomorrow it is charged 80%, from 10% to 90%. The sum of them is 110% or 1.1 charging cycle. Because charging/discharging profile can affect degradation profoundly, some other companies use weighted sum that may favor shorter charging periods or in favor of certain percentage range. For simplicity, the straightforward sum is used for this research.

Similar to usage rate, charging rate or charging cycle per month $C(t)$ is used here. It is a random variable that will also stay constant over the entire vehicle lifecycle. It is different from usage rate because of drivers' driving behavior differences. Usage rate only depends on how far a car is driven, and charging rate is also influenced by driving profile, such as accelerations and average speed. As shown in equation (4-3), a scaling factor $D(t)$ is created to scale the usage rate. When $D(t) = 1$, average driving profile is assumed. When $D(t) > 1$, it represents a more aggressive driver. When $0 < D(t) < 1$, it characterizes a less aggressive driver. The charging cycle limit is also first transferred to the warranty time dimension to generate the effective time, then compared with other two warranty dimensions to create effective warranty, as shown in equation (4-3).

$$C(t) = R(t)D(t)\frac{C_{lim}}{U_{lim}} \qquad (4\text{-}3)$$

$$EW = \min(T_{end}, U_{eff} / r, C_{eff} / c) \tag{4-4}$$

For the DES simulation, $D(t)$ is assumed to be an inverse normal distribution with mean at $\mu = 1$, and shape factor $\lambda = 20$, so $1/D(t)$ is normally distributed. It is also assumed that the car can drive 200 miles/charge cycle on average. The distributions are shown in Figure 4-6.

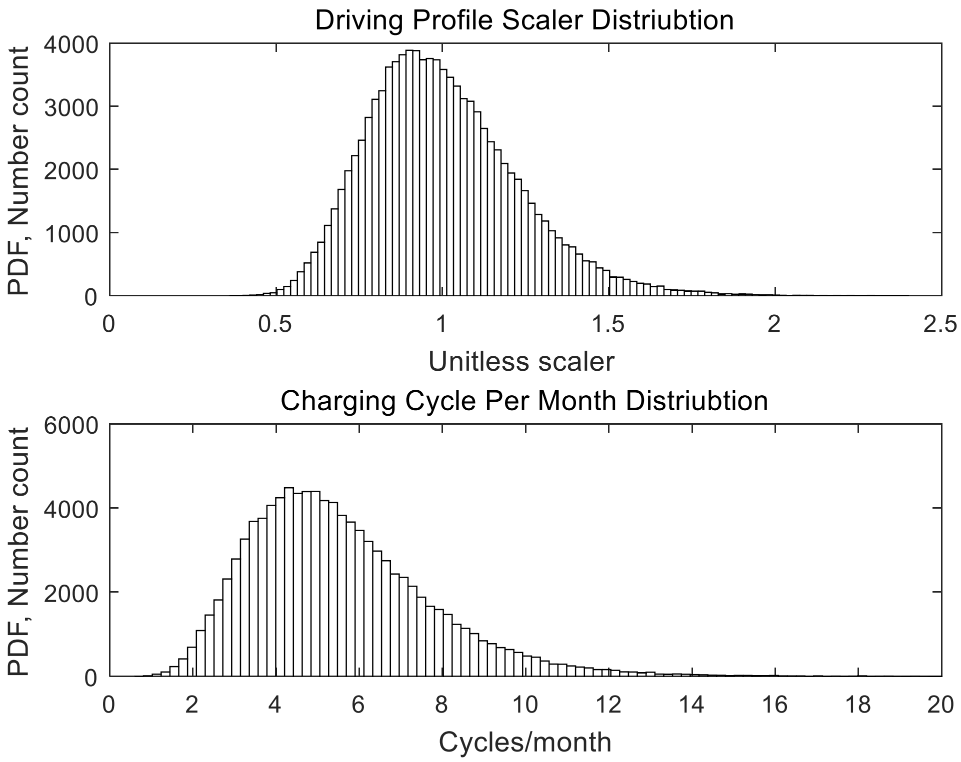


Figure 4-6. Distribution of driving profile scaler, D (top) and charging cycle per month, C (bottom).

The effect of changing the total number of charging cycles for warranty on both remanufacturing supply and demand curves is shown in Figure 4-7. It is evident that both supply and demand curves only shifted upward slightly in “return date" direction. This shift is mainly due to the fact that the charging cycles per month are highly dependent on usage rate, and effective warranty is also dependent on the other two warranty dimensions. However, as charging cycle limit increases, both supply and demand curves are shifted to low "RUL" direction. This shift is due to the increasing likelihood of module degradation failures. Intuitively, if more charging cycles are allowed (relative to driving distance and usage time), more aggressive driving (higher acceleration, higher speed) will more likely be included. For these more aggressive drivers, module degradation failures are more likely to occur.

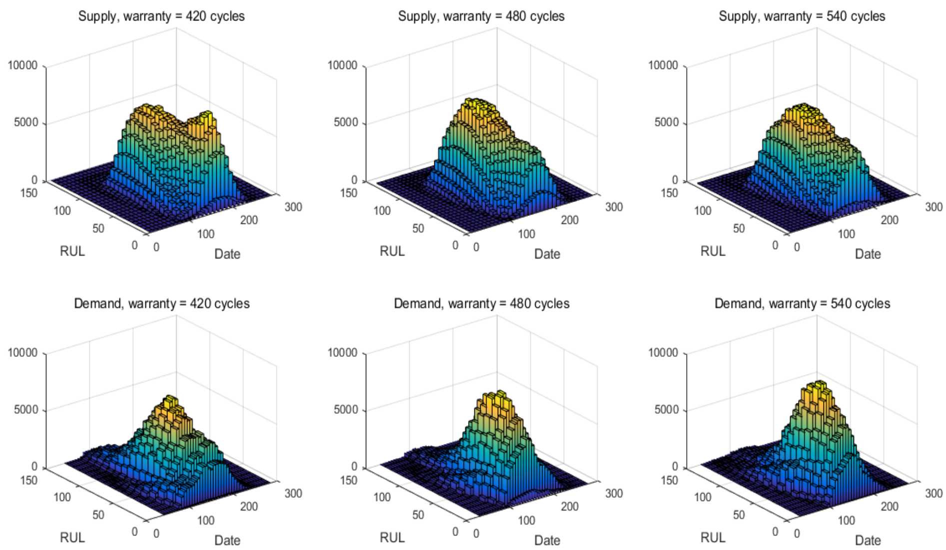


Figure 4-7. Effects of changing total warranty charging cycles on supply and demand. Both RUL and Date are in months.

4.5.4 **Inventory Policies**

Unlike other types of policies, inventory policy only changes supply curve.

This gives managers the freedom to plan the demand curve first, then adjust supply accordingly. Essentially, by changing different inventory policies, supply curve can be shifted in the "return date" direction. That is, the new supply time can be viewed as the sum of original supply time and storage time. Ideally, if the managers can obtain a perfect prediction of demand at different RUL levels, they can shift supply accordingly to have a perfect fit. However, because demand cannot be predicted flawlessly, different inventory policies need to be tested, and are discussed in this section. Here, the inventory is assumed to be first-in-first-out (FIFO).

Three types of inventory policies are considered.

- To store everything as in previous sections.
- To divide RUL levels into categories, and set different quantity limitations (inventory cap) on different categories. If a limit is reached, new supply of this category will be discarded.
- To divide RUL levels into categories again, and set different time limitations on different categories. If a module is stored pass the time limitation, it is discarded.

For this section, all simulation parameters are the same as in section 4.4.3, and only inventory parameters are different. It is assumed RUL only ranges from zero to 150 months. Either 5 categories (30 months per category) or 10 categories (15 months per category) are tested. The limitations are optimized using genetic algorithm that will be explained in more detail in the next section. The result is shown in Table 4-4. This optimization is achieved mainly by reducing the storage cost for unnecessary remanufactured modules. The percentage of supply used and demand satisfied is additionally improved because more modules with the right quality are stored.

Table 4-4. Market life cost by different inventory policies.

	Store everything	**Inventory Cap**		**Time limitation**	
		5 categories	**10 categories**	**5 categories**	**10 categories**
Percent supply used (%)	47.90%	58.24	59.42	60.28	60.51
Percent demand satisfied (%)	58.24%	69.3	72.49	68.43	72.88
OEM average cost ($)	6129.25	5698.43	5519.39	5643.19	5473.43
Customer average cost ($)	6724.87	6409.45	6289.31	6339.85	6243.02
OEM + cust. average cost ($)	12854.12	12107.88	11808.7	11983.04	11716.45
OEM total cost ($B)	0.61	0.57	0.55	0.56	0.55

4.5.5 **Optimization**

For the optimization problem, different combinations of policies are considered. For repairing and remanufacturing polices, matching with smallest suitable RUL and using most available module are considered. For warranty polices, the charging cycle limit ranges from 400 to 550 with increment by 10. For inventory policies, inventory limitations and time limitations are considered, and both 5-category and 10-category types are tested. Two objective functions are used. One is the total OEM cost during the entire market life, and the other is the sum of both OEM and all customers' costs during the entire market life. One is from manufacturer/remanufacturer's perspective, and the other is from society's perspective. Standard non-negative constraints are used.

A global mixed integer optimization algorithm, genetic algorithm, is used because the optimization problem may be non-linear and non-differentiable in nature, and several variables are discrete. Because of DES simulation programming complexity, two repairing/remanufacturing policies are ran separately and the results are combined to obtain the final solution. It is illustrated in Table 4-5 that the charging cycle limit is the binding factor (limited by the charging cycle range restrictions) for OEM cost minimization. However, if warranty terms are set too strictly, customers and media will doubt the quality and reliability of the product. On the other hand, OEM plus customer cost minimization seems to take another extreme on the spectrum. The result additionally shows that the inventory capacity limitation is in favor for both minimization objectives. Other observation is that the average OEM plus customers' costs are very similar for both objectives. This similarity may be caused by the rapid increasing in lower RUL portion and rapid decreasing in higher RUL portion in for both supply and demand curves. Thus, when overlapping them, "boundaries" are significant.

Table 4-5. Optimization results.

Objective function	OEM	OEM + customer
Percent supply used (%)	62.42	62.84
Percent demand satisfied (%)	74.39	74.45
OEM average cost ($)	5215.87	5245.59
Customer average cost ($)	6084.59	5858.94
OEM + cust. average cost	11300.46	11104.53
repair/reman policy	RUL	RUL
Charging cycle limit	400	530
Limitation	Inv. Cap	Inv. Cap
Category 1	103,697	111,292
Category 2	118,864	147,617
Category 3	130,016	135,059
Category 4	139,153	144,303
Category 5	37,645	72,041
Category 6	70,840	45,442
Category 7	40,833	31,113
Category 8	13,096	11,259
Category 9	980	2,292
Category 10	2,262	1,393

4.5.6 **Major Assumptions for Matching**

There are also a number of assumptions associated with the matching process.

- No degradation during storage. It is reported batteries degrades even when they are sitting on the shelf. However, it is small comparing to the degradation while driving.
- Only one generation of batteries. This means modules are exchangeable.
- No geographical consideration. Essentially, it is assumed all the batteries are stored and remanufactured in one place and perfect information sharing between repairing centers, so they know if there is a remanufactured

module with right RUL for them to use.

4.6 Conclusion

An EV battery pack remanufacturing discrete event system simulation study is performed in order to explore the feasibility of lowering the total market lifetime cost for both EV OEM and customers via remanufacturing automotive components. Several influential factors are considered, such as warranty, different battery failure modes and driving behavior. Key factors are also used for optimization, such as repairing and remanufacturing strategies and inventory policies. Although there are a number of aspects of the remanufacturing process that are not included in this study (many of them are listed in the assumption sub-sections at the end of supply, demand and matching segments), this study provides a good understanding of how a remanufacturing process may behave in real-life settings.

CHAPTER 5

Conclusion and Future Work

5.1 Conclusion and Contributions

This dissertation focuses on creating the "loop" between a remanufacturing system, customer and a manufacturing system. The major achievements of this dissertation can be summarized as follows.

In Chapter 2, the "quarter loop" is created. Namely, the loop between manufacturer and customer is formed. The remanufacturing supply side is studied. Instead of treating core return as completely random, a more regulated scheme through warranty is considered. Instead of using disaggregated approach, such as time series, a new aggregated approach of remanufacturing supply forecast is provided. An analytical model is stated and verified by discrete event simulations.

In Chapter 3, the "half loop" is created. Again, the "loop" links manufacturer and customers. Unlike Chapter 2, both the remanufacturing supply and demand sides are considered here. The four types of costs for the warranty are illustrated: single item cost to OEM, single item cost to customer, aggregated cost to OEM and cost schedule for OEM. All the influential factors in Chapter 2 are considered. In addition, warranty and battery degradation processes and failure processes are considered.

In Chapter 4, the “full loop” is created. All three parties; the manufacturer, customer and remanufacturer are included. Different supply-demand matching approaches are considered, such as a new warranty dimension policy, different repair and remanufacturing polices and different inventory policies. An optimization model using the above policies is provided.

Comparing with other remanufacturing researches, this study expands the existing remanufacturing system to including customers and manufacturing system, and a holistic approach is provided. The academic contributions of this research can be summarized as follows.

Unlike traditional manufacturing, remanufacturing processes need to make a closed loop approach between customers and manufacturers/remanufacturers. The traditional view of “supply-side” and “demand-side” does not necessarily apply because customers can be both “demand-side” of products and “supply-side” of returned cores. Similarly, a manufacturer/remanufacturer can also be both the “demand-side” and “supply-side.” The border between these two parties can be blurry depending on one’s view point. It becomes natural to include both sides into one system. This research, rather than treating customers’ behavior as uncontrollable events like many other remanufacturing research, it aims at influencing customers through warranty and other contracts.

Furthermore, this dissertation considers both quality and quantity attributes for both demand and supple of remanufactured goods. Unlike traditional manufacturing, the essence of remanufacturing is to turn the returned core of various quality levels to a better or higher quality level finished goods. Thus, when characterizing both the demand and supply for remanufacturing, quality is a critical attribute. Yet, it is not considered thoroughly in preceding research. In addition, the relationship between return date and the quality of return cores is also studied. This provides a more realistic and useful estimation for the supply side.

Once quality and quantity variations are considered, it is natural to provide a matching mechanism to ensure the right quality and quantity from both supply-side and demand-side are met. Chapter 4 provides a number of such matching mechanisms, such as different inventory storage policies, repairing policies, and warranty types. Chapter 4 also shows that matching mechanisms are essentially used to shift various categories of returned cores along the quality axis and return date axis of the three-dimensional demand and supply curves. By employing different matching mechanisms, the cost of remanufacturing can be dramatically lowered. Traditionally, variations in production systems are dealt with buffers. Buffers may be storage, capacity, time, profit, investment and many other types of manufacturing related characteristics. Essentially, buffering is to add additional capability or abilities to filter out the fluctuations. Storage, or inventory, is used to shift past production capacity (already produced parts) to an instance in the future. Investments and loans are shifting future virtual capacity (money from future sold products) to the past. Capacity buffer is to install additional devices in parallel.

Time buffer is to increase the order wait time or back order size. Similar to opportunity cost, time buffer essentially uses the wait time as opportunity capacity. From using “passive” buffers, this research explores the possibility of using different “active” matching mechanisms to cope with variations, and provides additional means to reduce the effects of those variations.

Diverse types of costs are also considered, such as single item cost to manufacturer, single item cost to customer, aggregated cost to manufacturer, aggregated cost schedule. Hence, a more holistic picture is provided for manufacturers, customers and regulators. Because of the cost schedule, quarterly, monthly, and weekly remanufacturing plans can be established.

A novel genetic based matching algorithm was additionally developed to minimize the total cost for manufacturers. This algorithm is capable of mixed categories and employs variable optimization which is suitable for the matching process.

5.2 Proposed Future Work

Chapter 4 listed a number of assumptions for all supply side, demand side and matching mechanisms. Relaxing any of them can be a new research direction. Major future work directions can be:

1. Different battery generations can be considered. Some generations can be only backward compatible, while other generations can provide both forward and backward compatibility.

2. Include geographic considerations. Currently, the entire world is treated as a single zone. It is unrealistic to ship battery packs from Asia to North America or to Europe. Different zones can be considered.
3. Second hand EVs can be studied. Many factors can be different, such as warranty, usage rate, degradation, trading between ownerships and so on. This will affect the dynamics of both the supply and demand sides.
4. Realistic failure and degradation processes can be considered. Weibull distribution is used for almost all failure and degradation processes. This simple approach may not capture everything realistically.

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