Reusability Assessment of Lithium-Ion Laptop Batteries Based on Consumers Actual Usage Behavior

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In this paper, a data set of Lithium-ion (Li-ion) laptop batteries has been studied with the aim of investigating the potential reusability of laptop batteries. This type of rechargeable batteries is popular due to their energy efficiency and high reliability. Therefore, understanding the life cycle of these batteries and improving the recycling process is becoming increasingly important. The reusability assessment is linked to the consumer behavior and degradation process simultaneously through monitoring the performance of batteries over their life cycle. After capturing the utilization behavior, the stability time of batteries is approximately derived. The stability time represents the interval that a battery works normally without any significant drop in performance. Consequently, the Reusability Likelihood of batteries is quantified using the number of cycles that the battery can be charged with the aim of facilitating future remarketing and recovery opportunities. [DOI: 10.1115/1.4031654]

1 Introduction

Product reusability is often a function of physical deterioration and technological obsolescence. The potential of product reusability has been studied from different perspectives ranging from the "design for reuse" [1], to the estimation of reliability and the remaining useful life (RUL) of a product [2], and the economic assessment of reuse decisions [3].

Although the discussion on product reusability is not new and the potential economic and environmental impacts of product reuse has been already discussed by prior studies, the research on analyzing consumers' behavior during previous life cycles and the impact of the intensity of using a product was subject to on the future reusability of multilifecycle products is very limited. To overcome this gap, the current study aims at assessing the future reusability of products through investigation of the actual product usage over previous life cycles and the product degradation process.

Different quantitative methods have been developed to estimate products' RUL using the technical and actual life information [4]. In addition, product reusability has been the point of interest at the early stages of product design with the aim of environmental impacts reduction [5,6]. Pricing policy and second-hand market value estimation are other topics related to the reusability assessment [7]. Moreover, some studies have focused on analyzing the associated costs of product reuse [8]. Although methods have been suggested for assessing product reusability, studies that consider the impact of consumer behavior on the reusability assessment and EoU/L recovery are limited [9,10].

To be more specific about the reusability of Li-ion batteries, several studies have designed different experiments representing the actual working conditions to analyze the life cycle of Li-ion batteries, as one of the most important feature of these batteries. Battery age and temperature are among the common factors employed in those experiments [11]. Another group of studies is those which have provided different estimation methods on identifying batteries state of health, state of charge, and capacity loss [12].

Although previous studies have tested various degradation and aging mechanisms under different conditions, sometimes spending several years of experimentation, to the best of our knowledge no study has reported any analyses on the performance of Li-ion batteries based on the actual dataset of consumer behavior profiles over several years of usage. The reusability assessment should be done combining both the consumer usage behavior and technical degradation process.

2 Dataset: Li-Ion Laptop Batteries

To assess the product reusability, the consumer behavior and product degradation process, a dataset of 507 same-brand Li-ion laptop batteries has been collected from an all-girl high school located in Burbank, IL. The technical and performance information of batteries have been gathered annually over their lifetime. The operating systems are enabled to report the used cycles and health status of Li-ion batteries. The battery technical characteristics include current weight, serial number, manufacturer, type (model), battery internal voltage, used cycles (the used charge–discharge cycles out of the maximum theoretical number of available cycles), full charge capacity (FCC, current fully charge capacity), status (dead or functional), design capacity (theoretic maximum charge capacity), usage time, class (user), and record date (the time that the battery characteristics are measured).

3 Analysis of Consumer Behavior: Battery Usage Cycles Over Time

The way in which a battery is used may influence its current and future performance. To reveal the impact of consumers' behavior, the number of used cycles for batteries is analyzed for different classes of students over 3 years of usage. Figure 1(*a*) shows the distribution of used cycles for all batteries with different ages. Used cycles refer to the number of times that the FCC of a battery has been used.

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As mentioned before, any battery can theoretically be used for a limited number of charge–discharge cycles. Looking at this distribution, we can conclude that this is not a unimodal continuous distribution. Before fitting appropriate distributions, it would be useful to see the students' behavior over the annual usage periods, their individual years of education. Therefore, the data have been separated into different groups based on two factors: (1) the years of usage (first year of battery usage, second year, and third year) and (2) the student class (class of 2011, 2012, 2013, 2014, 2015, and 2016). The resulting eight histograms and the best fitted distributions of the used cycle are depicted for different classes and years of usage in Figs. 1(*b*)–1(*d*). The best distribution is chosen based on the highest *p*-value of Goodness-of-Fit tests run for different distributions. The descriptive statistics of battery usage by different classes of students are summarized in Table 1. To avoid prolixity, the four resulting histograms of used cycles have been compared using confidence intervals for the first year of usage (Fig. 2).

The overlap between the 95% confidence intervals of different classes for the same year of usage illustrates the consistent behavior among different classes of students. Although there is a difference between classes 2012 and 2015 for the first year of usage, this might be assigned to different battery designs used by these two classes. Considering this point, the student class factor has been discarded and the data has been categorized into three groups based on the age of batteries regardless of the classes.

The number of used cycles during the lifetime of a battery is represented by random variable X_i. To further clarify, $X_{1\text{year}}$ is the total number of cycles that consumer has used during the first year of usage. The best statistical distributions have been fitted to the number of used cycles for each year employing Kolmogorov–Smirnov Goodness-of-Fit test. As seen, the number of used cycles follows lognormal distributions with the following parameters:

$$X_{1\text{year}} \sim \text{Log} - N(4.83,\ 0.14) \quad (1)$$

$$X_{2\text{years}} \sim \text{Log} - N(5.60,\ 0.14) \quad (2)$$

$$X_{3\text{years}} \sim \text{Log} - N(5.90,\ 0.14) \quad (3)$$

The *p*-values are 0.91, 0.056, and 0.44, respectively. The expected life of usual Li-ion batteries is estimated to be in the range of 300–500 cycles (although it depends on the technology and usage conditions). Thus, the battery will reach this threshold in 3 or 4 years according to the revealed consumer behavior. Later, we will consider 300 cycles as the threshold for Li-ion batteries performance maintaining.

4 Product Degradation Process

After analyzing the average usage of batteries over several years as discussed in Sec. 3, the next step is to study the design aspect, and more specifically, the degradation process of Li-ion batteries. This degradation could be described by several characteristics such as the relative capacity, which equals (FCC/design capacity) × 100, and the amount of energy stored inside the battery. FCC represents the actual capacity of a battery over time.

The process of laptop Li-ion batteries degradation can be analyzed through Figs. 3 and 4. It should be noted that there are some variations in the values of battery technical characteristics, even for batteries with the same design. To provide better insights, the analysis is shown for type A battery.

Type A has the lowest design capacity (*mAh*), while type D has the largest. This figure reveals that the first 300 cycles can be regarded as the stable lifetime before the performance drops significantly. This threshold is selected roughly based on industry experts opinion for the current dataset, and it can generally change based on the technology progress. Therefore, a threshold of 300 cycles has been considered for the maximum available cycles, represented by Ω. A more precise value for threshold can be obtained through statistical methods.

The observed variation in the technical characteristics is due to different usage conditions and the impacts of controllable and uncontrollable factors such as the ambient temperature, the recharging habit, and amount of chemicals inside the cells.

5 Reusability Likelihood Assessment

The likelihood of reusability is defined as the chance of reusing the battery for the last remaining *n* cycles before it reaches the threshold value Ω. The first step of likelihood assessment is to calculate the probability that consumers have used the battery at most Ω–*n* cycles during the past *i* years as follows:

$$A_i(n, \Omega) = \Pr(X_i \le \Omega - n), \ \ \forall i = 1, 2, \ \text{and}\ 3\ \text{years} \quad (4)$$

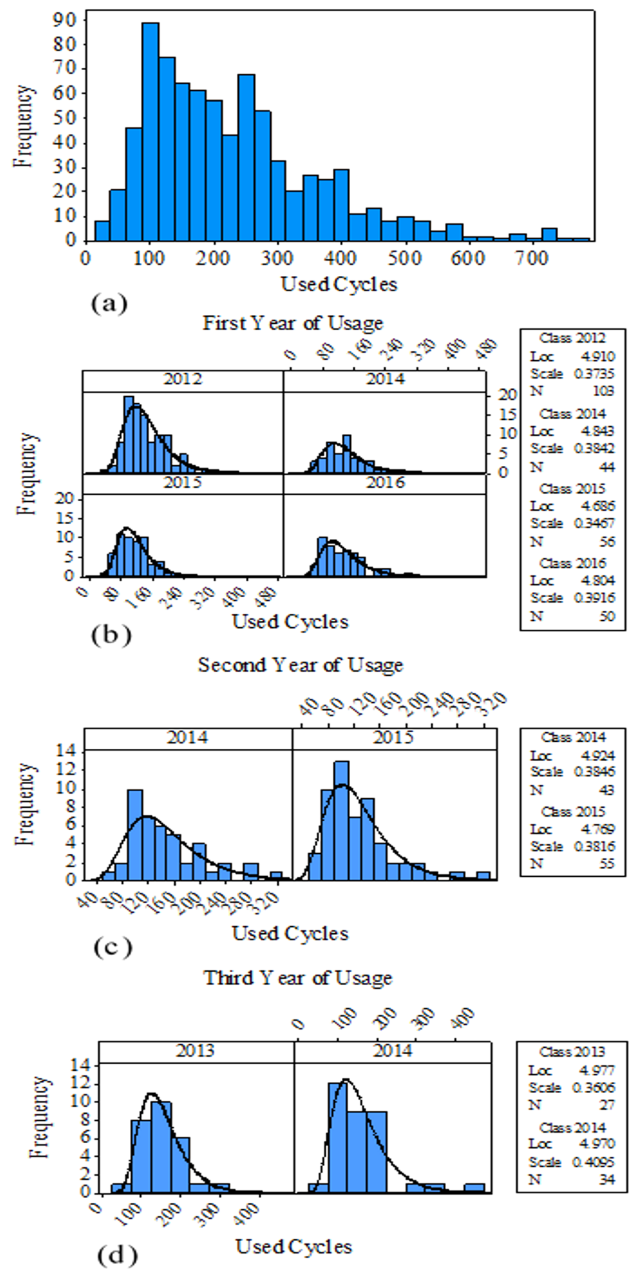

Fig. 1 The distribution of used cycles of all batteries: (*a*) The histograms of used cycles by different classes of consumers through the first year (*b*), second year (*c*), and third year (*d*) of batteries usage

Table 1 Statistical summary of the used cycles for different classes

	First year of usage				Second year of usage				First and second years of usage				Third year of usage			
Class	Number	Mean	St dev	IR[a]	Number	Mean	St dev	IR	Number	Mean	St dev	IR	Number	Mean	St dev	IR
2011	—	—	—	—	—	—	—	—	112	282.08	85.19	119.75	—	—	—	—
2012	103	145.05	53.39	72	—	—	—	—	—	—	—	—	—	—	—	—
2013	—	—	—	—	—	—	—	—	28	292.5	145.4	166.3	27	154.02	55.6	73
2014	44	136.02	51.86	56.25	43	148.07	59.61	75	—	—	—	—	34	157.4	77.3	70
2015	56	114.86	39.14	57	55	127.04	53.84	55	—	—	—	—	—	—	—	—
2016	50	131.54	52.61	76.75	—	—	—	—	—	—	—	—	—	—	—	—

[a]The interquartile range (IR) is the difference between the third and first quartiles that measures the variability.

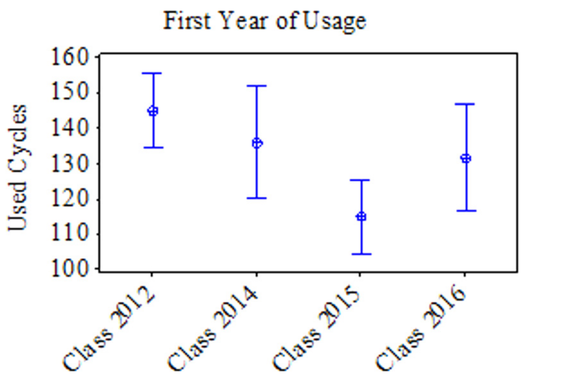

Fig. 2 The 95% confidence interval plots of the used cycles for the first year

In Eq. (4), $A_i(n, \Omega)$ is the probability that the battery has at least n more cycles for reusing. For example, the shaded area in Fig. 5 shows the probability that a 1-year old battery has been used less than 200 cycles. Since Ω is the threshold for the number of cycles, this probability represents the chance that the battery can be used for at least 100 more cycles. Looking at the mean of distribution, a 3-year old battery has almost been used for more than 300 cycles and the probability that it has been used less than 300 cycles is so low. So far, we have discussed the minimum potential number of available cycles. The next question might be: Is the battery guaranteed to survive beyond n?

To answer this question, an exponential-based survival function, $S(n)$, has been defined. The survival function represents the probability that the used battery survives beyond n cycles. Using the information of 19 dead batteries, the value of λ (the average number of used cycles to meet the first failure) is estimated as 2×10^{-3} 1/cycle or 500 cycles for the mean cycles to failure. We use the estimator that minimizes the mean square error.

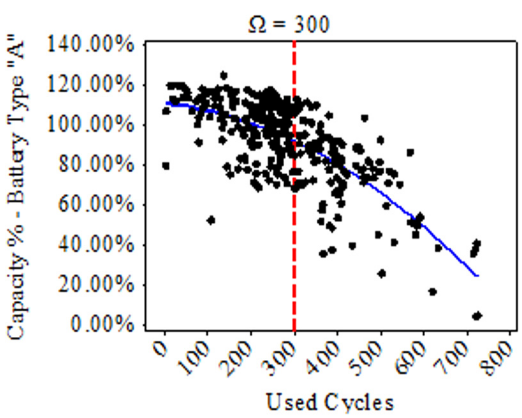

Fig. 3 The degradation of type A batteries performance based on the number of used cycles. Here, capacity % equals [FCC/design capacity] × 100.

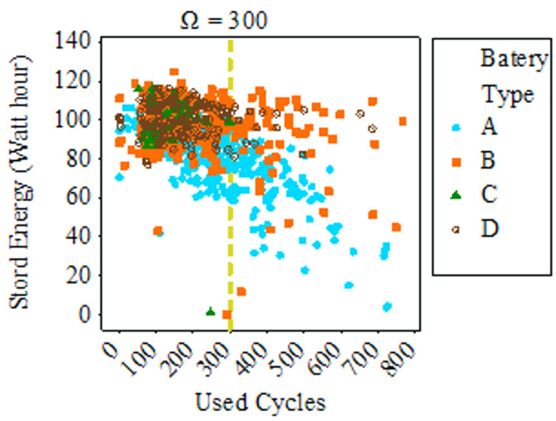

Fig. 4 The degradation trend in the energy capacity of batteries across the used cycles

$$\hat{\lambda} = \frac{n-2}{\sum_{i=1}^{n} C_i} \tag{5}$$

In Eq. (5), C_i is the number of used cycles before failure. Therefore, the likelihood of reusability (See Fig. 6) can be derived as follows:

$$\hat{L}_R^i(n,\ \Omega) = A_i(n, \Omega) \times S(n), \ \ \forall i = 1, 2, \text{ and } 3 \text{ years} \tag{6}$$

$$\hat{L}_R^i(n,\ \Omega) = \Pr(X_i \le \Omega - n) \times \Pr(Y > n), \ \ \forall i = 1, 2, \text{ and } 3 \text{ years} \tag{7}$$

$$\hat{L}_R^i(n,\ \Omega) = \Pr(X_i \le \Omega - n) \times e^{-\lambda n}, \ \ \forall i = 1, 2, \text{ and } 3 \text{ years} \tag{8}$$

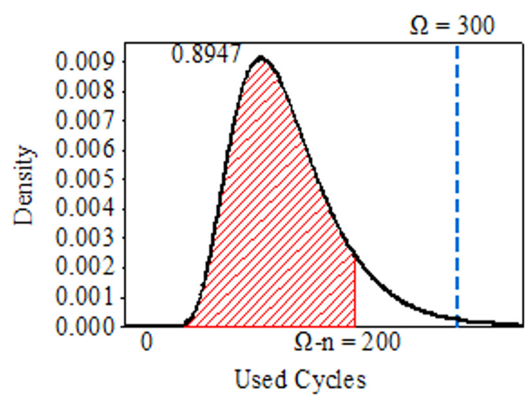

Fig. 5 The graphical representation of *A*(200, 300) for a battery that has been used for 1 year

6 Reusability Economics

The reusability assessment approach can be applied in calculating the profitability of remanufacturing systems. The best recovery option for the returned product varies depending on the quality, functionality, and reusability of that product. For simplicity, consider a system in which remanufacturing, refurbishing, and material recovery are all possible recovery alternatives. The question is whether to remanufacture, refurbish a used item, or send it for material recovery?

A fixed profit for material recovery option and a linear profit function of n (remaining cycle for reusing) for remanufacturing and refurbishing profit have been assumed. Equation (9) represents the age-based expected profit of remanufacturing for a Li-ion battery with different age values (1, 2, and 3 years). The remanufacturing cost value is equal to $\kappa \times (\Omega - n)$, where κ (\$/cycle) > 0 is the unit adjustment cost of remanufacturing. υ (\$/cycle) is the unit adjustment price for remanufactured product determined by remanufacturers. A remanufactured battery is essentially the same as a new one. The second option would be refurbishing. In this case, the used Li-ion battery is sold as is without any major recovery actions. Therefore, the next consumer can reuse it for the remaining n cycles and only pays for the remaining available cycles. Similar to υ, α (\$/cycle) is the unit adjustment price for refurbished product. Then, the age-based expected profit value for these three options can be represented as follows:

$$E\left(P^i_{\mathrm{RM}}\right) = \int_0^{\Omega}\left[-\frac{d}{dn}A_i(n,\Omega)\right] \times [\upsilon \times \Omega - \kappa \times (\Omega - n)]dn, \ \forall i = 1, 2, \text{ and } 3 \text{ years} \tag{9}$$

$$E\left(P^i_{\mathrm{RF}}\right) = \int_0^{\Omega}\left[-\frac{d}{dn}A_i(n,\Omega)\right] \times (\alpha \times n)dn, \ \forall i = 1, 2, \text{ and } 3 \text{ years} \tag{10}$$

$$E(P^i_{\mathrm{MR}}) = \rho, \ \forall i \geq 0 \tag{11}$$

It can be observed that increasing the value of Ω (increasing the durability of product) will increase the age-based expected profit of both remanufacturing and refurbishing options (Fig. 7). So far, what has been discussed was the age-based expected profit. To calculate the unconditional expected profit, the condition of returned batteries to recovery system (age) should be known. Let us consider w_i as the percentage of all batteries with the same age i. It is assumed that the expected value of a battery with age more than 3 years is approximately zero. Then, the expected profit value for each recovery option can be obtained as follows:

$$E(P_{\mathrm{RM}}) = \sum_{i=1}^{\infty} w_i \times E(P^i_{\mathrm{RM}}) = \sum_{i=1}^{3} w_i \times E(P^i_{\mathrm{RM}}) \tag{12}$$

$$E(P_{\mathrm{RF}}) = \sum_{i=1}^{\infty} w_i \times E(P^i_{\mathrm{RF}}) = \sum_{i=1}^{3} w_i \times E(P^i_{\mathrm{RF}}) \tag{13}$$

$$E(P_{\mathrm{MR}}) = \sum_{i=1}^{\infty} w_i \times E(P^i_{\mathrm{MR}}) = \rho \tag{14}$$

The expected profit not only depends on the type of recovery option, but also on the pricing policy. To address the price policy question, an optimization model is developed by considering the market demand affected by the price. The demand percentage for the remanufactured and refurbished items is quantified through Eq. (15), where E_{RM} and E_{RF} are the positive price elasticity demand for the remanufactured and refurbished batteries

$$\begin{aligned} D'_{\mathrm{RM}} &= 1 - E_{\mathrm{RM}} \times \upsilon \\ D'_{\mathrm{RF}} &= 1 - E_{\mathrm{RF}} \times \alpha \end{aligned} \tag{15}$$

where

$$\left\{1 \leq E_{\mathrm{RM}} \times \upsilon + E_{\mathrm{RF}} \times \alpha, \ \ \upsilon \leq \frac{1}{E_{\mathrm{RM}}}, \alpha \leq \frac{1}{E_{\mathrm{RF}}}\right\}$$

If the total demand percentage for the remanufactured and refurbished batteries is less than one, the rest of batteries will be sent to material recovery. Therefore, the objective function (total profit) can be calculated based on the total number of batteries returned for recovery, r, the percentage of batteries sent to each recovery option (demand) and the expected profit of each option

$$\text{maximize} \quad Z = r \times (1 - E_{\mathrm{RM}} \times \upsilon) \times E(P_{\mathrm{RM}}) + r \times (1 - E_{\mathrm{RF}} \times \alpha) \times E(P_{\mathrm{RF}}) + r \times (E_{\mathrm{RM}} \times \upsilon + E_{\mathrm{RF}} \times \alpha - 1) \times \rho \tag{16}$$

subject to

$$\begin{gathered} 1 \leq E_{\mathrm{RM}} \times \upsilon + E_{\mathrm{RF}} \times \alpha \\ \upsilon \leq \frac{1}{E_{\mathrm{RM}}} \\ \alpha \leq \frac{1}{E_{\mathrm{RF}}} \\ \upsilon, \alpha \geq 0 \end{gathered}$$

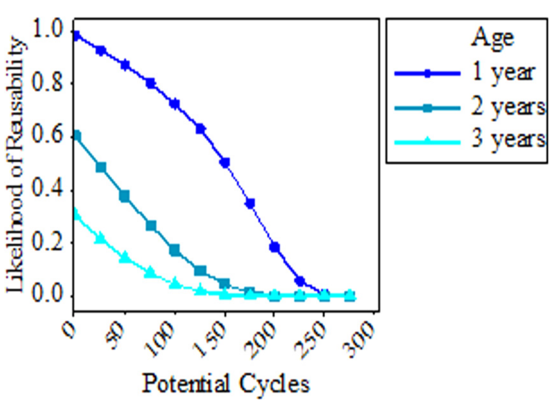

Fig. 6 Estimation of reusability likelihood for batteries that have been used for 1, 2, and 3 years

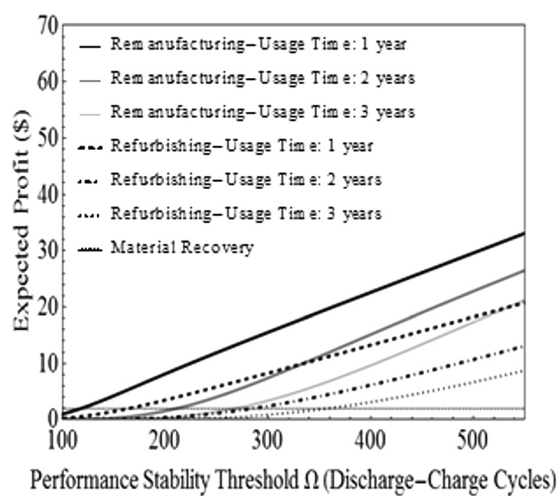

Fig. 7 The age-based expected profit of remanufacturing, refurbishing, and material recovery options based on Ω for a 1, 2, and 3 years old Li-ion battery

Table 2 The closed-form optimal solutions for the proposed model

	υ^*	α^*	$Z^*(\upsilon^*,\alpha^*)$	Feasibility criteria
Case 1	$\dfrac{E_{\mathrm{RM}}\kappa Z+T+E_{\mathrm{RM}}\rho}{2E_{\mathrm{RM}}T}$ [a]	$\dfrac{H+E_{\mathrm{RF}}\rho}{2E_{\mathrm{RF}}H}$	$\dfrac{r\left(E_{\mathrm{RF}}HT^2+E_{\mathrm{RM}}{}^2E_{\mathrm{RF}}H(\rho+\kappa Z)^2+E_{\mathrm{RM}}T\left(H^2+E_{\mathrm{RF}}{}^2\rho^2-2E_{\mathrm{RF}}H\kappa Z\right)\right)}{4E_{\mathrm{RM}}E_{\mathrm{RF}}\mathrm{HT}}$	$F_{\text{case }1}=\left\{\dfrac{\kappa Z}{2T}+\dfrac{\rho}{2H}>0,\ \dfrac{E_{\mathrm{RM}}\kappa Z+T+E_{\mathrm{RM}}\rho}{2T}<1,\ \dfrac{H+E_{\mathrm{RF}}\rho}{2H}<1\right\}$
Case 2	$\dfrac{1}{E_{\mathrm{RM}}}$	$\dfrac{1}{E_{\mathrm{RF}}}$	$r\rho$	$F_{\text{case }2}=\{E_{\mathrm{RM}}\kappa Z+E_{\mathrm{RM}}\rho>T, E_{\mathrm{RF}}\rho>H\}$
Case 3	$\dfrac{E_{\mathrm{RM}}\kappa Z+T+E_{\mathrm{RM}}\rho}{2E_{\mathrm{RM}}T}$	$\dfrac{1}{E_{\mathrm{RF}}}$	$\dfrac{r\left(T^2+2E_{\mathrm{RM}}T(\rho-\kappa Z)+E_{\mathrm{RM}}{}^2(\rho+\kappa Z)^2\right)}{4E_{\mathrm{RM}}T}$	$F_{\text{case }3}=\left\{\dfrac{E_{\mathrm{RM}}\kappa Z+T+E_{\mathrm{RM}}\rho}{2T}<1,\ \dfrac{E_{\mathrm{RM}}\kappa Z+T+E_{\mathrm{RM}}\rho}{2E_{\mathrm{RM}}T}>0,\ E_{\mathrm{RF}}\rho>H\right\}$
Case 4	$\dfrac{1}{E_{\mathrm{RM}}}$	$\dfrac{H+E_{\mathrm{RF}}\rho}{2E_{\mathrm{RF}}H}$	$\dfrac{r(H+E_{\mathrm{RF}}\rho)^2}{4E_{\mathrm{RF}}H}$	$F_{\text{case }4}=\left\{E_{\mathrm{RM}}\kappa Z+E_{\mathrm{RM}}\rho>T,\ \dfrac{H+E_{\mathrm{RF}}\rho}{2H}>0,\ \dfrac{H+E_{\mathrm{RF}}\rho}{2H}<1\right\}$

[a] $H=\sum_{i=1}^{3}w_i\int_0^{\Omega}\left[-\dfrac{d}{dn}A_i(n,\Omega)\right]ndn,\ T=\sum_{i=1}^{3}w_i\int_0^{\Omega}\left[-\dfrac{d}{dn}A_i(n,\Omega)\right]\Omega dn,\ Z=\sum_{i=1}^{3}w_i\int_0^{\Omega}\left[-\dfrac{d}{dn}A_i(n,\Omega)\right](\Omega-n)dn.$

The Lagrange multipliers method has been used to solve the model. Since the objective function is a nonnegative linear combination of concave functions on the domain, it is a concave function as well. Therefore, the Karush–Kuhn–Tucker (*KKT*) conditions are both necessary and sufficient conditions for the optimality.

For any combination of parameters (Ω, κ, E_{RM}, E_{RF}, ρ, r, w_1, w_2, w_3), there is an optimal vector (υ^*, α^*, λ_1^*, λ_2^*, λ_3^*) which maximizes the profit function, as shown in Table 2.

A sensitivity analysis is done to show the impact of model parameters (price elasticity, cost of remanufacturing and cost of

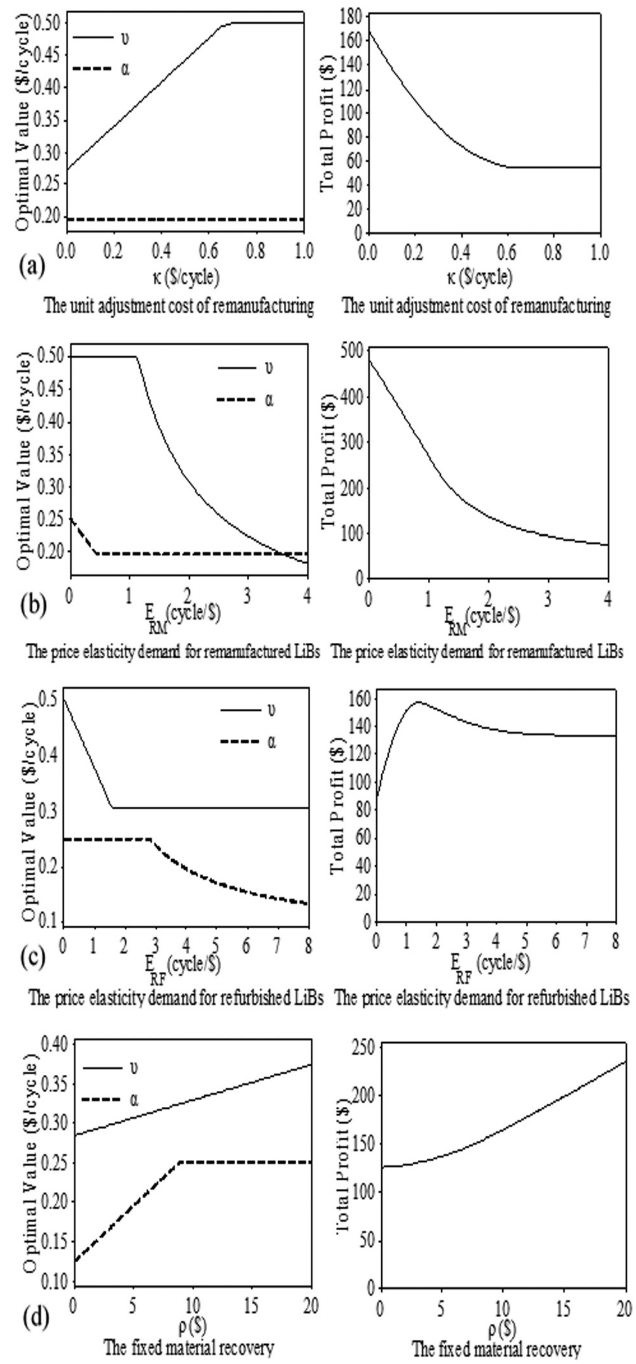

Fig. 8 The optimal profit function and prices behavior as one-way functions of Ω, κ, E_{RM}, with baseline values $\Omega = 300$ cycles, $\kappa = 0.1$ \$/cycle, $E_{\mathrm{RM}} = 2$ cycle/\$, $E_{\mathrm{RF}} = 4$ cycle/\$, $\rho = 5$\$, $r_A = 10$, $w_1 = 0.1$, $w_2 = 0.1$, $w_3 = 0.1$. (*a*) The unit adjustment cost of remanufacturing, (*b*) the price elasticity demand for remanufactured LiBs, (*c*) the price elasticity demand for refurbished LiBs, and (*d*) the fixed material recovery.

refurbishing) on the optimal price policy and the total profit. Figure 8 demonstrates the results of sensitivity analysis. In Fig. 8(*a*), as the cost of remanufacturing increases, the remanufacturer will increase the price of remanufactured battery. The total profit will monotonically decrease. Once the remanufacturing or refurbishing are not profitable, then the only option is material recovery which results into a fixed profit. When the elasticity values increase, the best policy would be reducing the prices (Figs. 8(*b*) and 8(*c*)). Similar to Fig. 8(*a*), the total profit will behave stationary after a threshold. Finally, the remanufacturer prefers to recover the material if the material recovery profit is sufficient.

7 Conclusion

This paper analyzed a data set of around 500 used Li-ion laptop batteries to provide insights on future reusability of batteries based on the battery's number of used cycles by previous consumers. Further, it has been shown how the reusability information can be employed to determine the most profitable EoU/L recovery plan and pricing policies.

For future study, the effect of reusability of product components on the RUL of the whole product can be analyzed and the market share can be estimated based on the reusability assessment. More data collection is needed to cover different categories of consumers and products. In addition, considering the uncertainty in market demands, its social and environmental impacts are another idea for future study as a strategic decision making problem.

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References

[1] Yang, Q., Yu, S., and Jiang, D., 2014, "A Modular Method of Developing an Eco-Product Family Considering the Reusability and Recyclability of Customer Products," J. Cleaner Prod., **64**, pp. 254–265.

[2] Zhang, Q., Tse, P. W.-T., Wan, X., and Xu, G., 2015, "Remaining Useful Life Estimation for Mechanical Systems Based on Similarity of Phase Space Trajectory," Expert Syst. Appl., **42**(5), pp. 2353–2360.

[3] Mashhadi, A. R., Behdad, S., and Esmaeilian, B., 2015, "Uncertainty Management in Remanufacturing Decisions: A Consideration of Uncertainties in Market Demand, Quantity and Quality of Returns," ASCE-ASME J. Risk Uncertainty Eng. Syst., Part B: Mech. Eng., **1**(2), p. 021007.

[4] Si, X.-S., Wang, W., Hu, C.-H., Zhou, D.-H., and Pecht, M. G., 2012, "Remaining Useful Life Estimation Based on a Nonlinear Diffusion Degradation Process," Reliab. IEEE Trans., **61**(1), pp. 50–67.

[5] Huang, J., Esmaeilian, B., and Behdad, S., 2015, "Multi-Purpose Disassembly Sequence Planning," ASME Paper No. DETC2015-46906.

[6] Behdad, S., Joseph, A. T., and Thurston, D., 2013, "Systems Simulation of Design for End-of-Life Recovery Under Uncertainty," ASME Paper No. DETC2013-12639.

[7] Kwak, M., Kim, H., and Thurston, D., 2012, "Formulating Second-Hand Market Value as a Function of Product Specifications, Age, and Conditions," ASME J. Mech. Des., **134**(3), p. 032001.

[8] Behdad, S., Williams, A. S., and Thurston, D., 2012, "End-of-Life Decision Making With Uncertain Product Return Quantity," ASME J. Mech. Des., **134**(10), p. 100902.

[9] Mashhadi, A. R., Esmaeilian, B., and Behdad, S., 2015, "Modeling Consumer Decisions on Returning End-of-Use Products Considering Design Features and Consumer Interactions: An Agent Based Simulation Approach," ASME Paper No. DETC2015-46864.

[10] Sabbaghi, M., Esmaeilian, B., and Mashhadi, A., 2015, "An Investigation of Used Electronics Return Flows: A Data-Driven Approach to Capture and Predict Consumers Storage and Utilization Behavior," Waste Manage., **36**, pp. 305–315.

[11] Tröltzsch, U., Kanoun, O., and Tränkler, H.-R., 2006, "Characterizing Aging Effects of Lithium Ion Batteries by Impedance Spectroscopy," Electrochim. Acta, **51**(8–9), pp. 1664–1672.

[12] Han, X., Ouyang, M., Lu, L., and Li, J., 2014, "A Comparative Study of Commercial Lithium Ion Battery Cycle Life in Electric Vehicle: Capacity Loss Estimation," J. Power Sources, **268**, pp. 658–669.