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Research Paper

Estimating energy left in discarded alkaline batteries: Evaluating consumption and recovery opportunities

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ABSTRACT

Each year, a significant number of single-use alkaline batteries with untapped energy are discarded. This study aims to analyze the usage patterns of alkaline batteries based on a dataset of 1021 used batteries, ranging from Size AA to 9V, collected from households in the State of New York. We measure the energy loss resulting from underutilized batteries and examine the corresponding environmental and economic impacts on a national scale. Discarded AA alkaline batteries maintain about 13 % of their initial energy, that results in an estimated annual energy loss of 660 MWh for all AA alkaline batteries in the U.S., and about 40 MWh in New York State. Annually in the U.S., consumers discard AA alkaline batteries with approximately $80 million worth of unused energy, including $4.8 million in New York State alone. We also show that the lifecycle impact of batteries should be multiplied by 1.25 to account for their underutilization. To address these issues, we propose actionable recommendations for improving battery consumption practices and facilitating End-of-Life/Use (EoL/U) recovery processes. The findings show the need for policy interventions to better manage battery usage and disposal toward reducing energy waste and mitigating environmental impacts.

1. Introduction

Given the current concerns on resource depletion, waste generation, and environmental degradation, analyzing consumer consumption behavior becomes important. One area worth investigation is the consumption of single-use alkaline batteries. On average, the per capita consumption of primary batteries in the U.S. stands at eight units annually according to a study (U.S. Environmental protection Agency, 2009). Single-use alkaline batteries constitute 80 % of the total primary batteries manufactured in the U.S. (Shin et al., 2020). Given the nation's population of about 330 million according to the U.S. Census Bureau, this aggregate usage corresponds to the disposal of approximately 2.11 billion single-use alkaline batteries on a yearly basis.

However, the utilization of the 2.11 billion alkaline batteries is not complete before disposal. Available evidence suggests that discarded alkaline batteries often retain residual energy at the time of disposal (Lee et al., 2021). Here, some questions arise: 1) To what extent do alkaline batteries retain residual energy when discarded by consumers? 2) What are the common patterns observed among consumers in the utilization of alkaline batteries? and 3) What are the economic and environmental impacts associated with the underutilization of alkaline batteries on a large scale?

This study provides an analysis of energy loss from underutilized single-use alkaline batteries. It also assesses the broader environmental and economic impacts on a national scale. The paper discusses the importance of incorporating usage patterns into lifecycle impact assessments. Moreover, it presents practical recommendations for improving alkaline battery consumption and EoL/U recovery processes.

To achieve the objectives of this study, we assess a sample of used single-use alkaline batteries. The technical characteristics of the batteries are measured and the dataset is used as input to our energy loss estimation model and conducting economic and environmental assessments. A summary of our findings shows that, 24 % of the collected batteries still retain significant energy. Approximately 17 % of the collected batteries have not been used, which indicates considerable inefficiencies in battery consumption. Based on the findings, we propose implementing a cascaded utilization guideline to improve consumer awareness of efficient battery usage, launching public awareness campaigns to highlight the environmental and economic advantages of extending battery lifespan before disposal, and adding energy displays

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to batteries as a means to facilitate informed consumer decision-making.

The remainder of this paper is organized as follows: In Section 2, we present an overview of the literature. The method is explained in Section 3, followed by a discussion of the battery samples in Section 4. In Section 5, we assess the technical characteristics of batteries, such as open-circuit voltage, loaded-battery voltage, and internal resistance. The results from Section 5 are used in Section 6 to estimate the energy left in the batteries. Section 7 provides the results of an environmental and economic impact analysis. In Section 8, we present a discussion on the findings from Section 7, along with suggesting recovery solutions for EoL/U alkaline batteries. Finally, Section 9 concludes the paper.

2. Literature review

We conduct a review of literature on consumer behavior regarding single-use batteries, the analysis of residual energy levels within these batteries, the potential for energy harvesting from remaining charge, and the energy, economic, and environmental impacts resulting from imperfect battery utilization. Based on the examination of existing research, we identify research gaps.

A stream of papers discusses consumer behavior and decision-making regarding household battery usage and disposal. For example, Islam et al. (2022) show that deposit return schemes and incentives such as old-for-new swaps encourage battery returns to collection centers. Duarte Castro et al. (2022) find that that awareness is key in influencing consumers' choice of appropriate battery disposal methods. Duarte Castro et al. (2022) also report that poor handling of waste batteries is mainly due to untrained and unequipped waste pickers, as well as too few collection points. Kalmykova et al. (2017) reveal that half of the batteries are disposed of within three years, with another 30 % within 3–11 years. Although alkaline batteries typically reach their EoL within a year (Song et al., 2017), they often remain in households long before disposal. Their performance is affected by temperature and storage conditions, with cold temperatures reducing reusability (Prauzek et al., 2018).

There exist studies on underutilization of rechargeable batteries. For example, Schneider et al. (2009) evaluate the capacity of discarded but still functional NiMH battery cells and find that approximately 37 % could be reused. In another study, Kamath et al. (2020) propose using second-life electric vehicle batteries for energy storage in fast-charging systems to reduce costs and environmental impact. In a different study, Steckel et al. (2021) explore using retired electric vehicle batteries for energy storage, highlighting their cost-effectiveness and suggesting policy incentives to promote adoption. Despite these insights, there is limited research on consumer use of single-use alkaline batteries.

Lee et al. (2021) explore a self-adaptive pulse discharge method for recovering and reusing energy from single-use alkaline batteries by achieving efficiencies of 33.49 % to 46.43 %. However, several challenges affect energy harvesting from semi-depleted alkaline batteries. There is a lack of data on the number and remaining energy of these batteries. Batteries packaged within products require dismantling for measurement (Saxena and Pecht, 2020). At the household level, non-technical users often need assistance to connect and use these batteries (Wei et al., 2016), and the limited number of batteries restricts the total recoverable energy. Also, households typically have only a few batteries, which further limits the potential for reuse.

Another section of relevant literature focuses on life cycle impacts and circularity assessments for single-use alkaline batteries, particularly post-disposal. For example, Hamade et al. (2020) find that reusing cathodes and anodes can lead to significant energy and CO_2 savings. Tran et al. (2018) examine the collection and recycling of spent alkaline batteries using various life cycle impact assessment methods, and find that recycling preserves metals but consumes more energy compared to incineration. V. Valdrez et al. (2022) simplify zinc extraction from used alkaline batteries by focusing on the anode, and achieved a 58 % recovery rate without complex purification, with low costs, and minimum environmental impact. Our life cycle assessment differs by incorporating uncertainty in battery utilization, which previous studies overlook. Dolci et al. (2016) find that using rechargeable batteries for 20 cycles or fewer can have higher environmental impacts than single-use alkaline batteries but they did not consider the inefficient use of single-use batteries. Our approach addresses the underutilization of alkaline batteries and facilitates comparison between single-use alkaline and rechargeable batteries in the future studies. We also contribute to the energy analysis of alkaline batteries, an area that has been less emphasized compared to the traditional focus on resources and environmental impacts.

While consumer behavior about battery disposal is well-studied, there is a lack of studies on single-use alkaline batteries' utilization and their energy left after they are discarded. In one recently published paper, Dai et al. (2023) propose a lightweight state-of-charge estimation method using Peukert's Law to estimate battery capacity and cumulative current consumption. In another study, Liu et al. (2024) present a new way to estimate battery charge that is more accurate and stable for different batteries and conditions, and have lower errors, especially under duty cycle loads. Both studies are conducted with implications for primary battery powered sensor nodes. However, analyzing the reuse of single-use alkaline batteries and their remaining energy at the household level has received limited attention. Finally, further investigation is needed to incorporate uncertainty in battery utilization into life cycle assessments. Overcoming these gaps will facilitate the development of more sustainable practices in alkaline battery usage, disposal, and recycling.

In summary, the literature review reveals various research gaps in the management of used alkaline batteries. The areas needing further investigation include, but are not limited to, the impact assessment of policy interventions on promoting responsible battery use and recycling, exploring opportunities for improving battery design to extend their lifespan, and analyzing consumer behavior and the impact of unsustainable battery use. Along this line, this study focuses on evaluating the energy, economic, and environmental impacts of single-use alkaline battery consumption.

3. Method

The first step of the proposed method includes the collection of a sufficiently large and representative sample of used single-use alkaline batteries. Careful consideration is given to factors such as collection regions to confirm that the battery sample accurately reflected the diversity of the population. Moreover, random sampling methods are used to minimize bias and improve the generalizability of the study's findings.

After the data collection and sampling procedure, the method includes a step for the assessment of the technical characteristics of the collected single-use alkaline batteries. This assessment consists of the measurement of critical parameters, including open-circuit voltage, loaded-battery voltage, and internal resistance. Utilizing specialized instruments such as battery impedance testers, load resistors, and digital multimeters facilitates the evaluation of battery health and performance. Each battery is assessed twice by two different research assistants for the measurement accuracy. If a significant difference in measurement is observed, the battery goes through a final test by both assistants to finalize its records.

The next step includes the estimation of the remaining energy within each battery. This estimation is performed based on a relationship between the remaining service hours, during which a battery can consistently supply a constant power rate, and its load voltage and internal resistance. Here, two approaches exist for determining the relationship. The first required conducting another experiment to gather data on remaining service hours. However, we choose the second method, where the relationship has already been established by the battery manufacturer. Once the remaining service hours are estimated, determining the remaining energy becomes a straightforward calculation involving the multiplication of the remaining service hours by the constant power rate.

The final step of the method evaluates the economic and environmental impact of inefficient battery consumption at a large scale. Analyzing these impacts at the state level and extrapolating findings to the national consumption of single-use alkaline batteries within the U.S., provide the broader implications of battery inefficiency in the country.

Our data from New York State can be extrapolated to the national level for several reasons. Our sampling strategy captures a diverse and representative sample of used single-use alkaline batteries from various regions within New York State, which is reflective of the overall diversity in the U.S. population. Also, we employ random sampling techniques to minimize bias and achieve a statistically representative of the national population of single-use alkaline batteries. The technical assessments, including measurements of voltage, resistance, and other critical parameters, are based on standardized methods and instruments that are widely accepted in the industry and academic literature. Furthermore, our estimation of remaining energy in batteries is based on established relationships provided by battery manufacturers and academic studies, with nationwide applicability.

In conclusion, the methodology used for assessing the technical characteristics of the batteries employs a representative sample as well as thorough measurement techniques. It uses the well-established method suggested by manufacturers for identifying relationships between battery parameters and estimating remaining energy. Nonetheless, there is room for improvements, such as expanding sampling regions and incorporating additional measurement methods to further address any remaining biases or inaccuracies.

4. Overview of battery samples

A sample of used batteries is collected in collaboration with the Coalition of Positively Charged People, a 501(c)(3) nonprofit organization based in the State of New York. This organization has conducted a series of events aimed at educating residents about the safe disposal of batteries. They collect used batteries from different collection events in New York and send them to the recycling facilities in Ohio and Michigan. Since its launch, the program has collected over 400 kg of batteries.

We use a systematic sampling approach using a 1-kg bucket to extract four random samples of batteries from four large boxes containing collected used batteries. The total number of batteries in the sample is 1021. The sample of batteries comprises 839 alkaline batteries, 7 ZnC batteries, 93 lithium-ion (Li) batteries, 17 nickel–cadmium (NiCd) batteries, 13 nickel–metal hydride NiMH batteries, 49 lead-contained (Pb) batteries, and 3 zinc chloride (ZnCl) batteries. Regarding battery size, there are 29 9V batteries, 706 AA batteries, 191 AAA batteries, 25C batteries, 69 D batteries, and 1 A23 battery. Of the batteries, 49.1 % are manufactured in China, 41.7 % in the U.S., and the remaining 9.2 % originate from Indonesia, Japan, Korea, Malaysia, Singapore, Thailand, Germany, or Canada. The group comprises batteries from 56 different brands, with 65.4 % of the 1021 batteries coming from two major battery vendors. Table 1 summarizes the distribution of samples per chemical/size group.

There are several points worth mentioning about the collection of batteries. The presence of 17 NiCd batteries and 13 NiMH batteries shows that, despite advancements in newer technologies such Lithium-ion and lithium-polymer batteries, certain devices continue to depend on these older battery types. Alternatively, it is possible that individuals still have old rechargeable batteries in their households, which contributes to their inclusion in the sample (Cherrier and Türe, 2023).

In addition, the presence of 49 Pb batteries shows the continued use of lead-acid batteries, which points out the importance of proper disposal and recycling due to environmental concerns associated with lead. Finally, the diversity in battery types emphasizes the significance of responsible waste management, as different battery chemistries require different recycling processes to recover materials and minimize environmental impact.

The focus of this study is on single-use alkaline batteries, the most frequently observed model in our collected samples (839 out of 1021). This scope provides a detailed technical analysis and tailored recommendations for one of the most widely used battery types. To have a randomized sampling process, we use the 1-kg bucket method to extract two samples from a total of 839 alkaline batteries collected. Therefore, the final sample consists of 485 batteries, including 246 AA, 116 AAA, 25C, 68 D, and 30 9V batteries. These quantities facilitate an examination of energy levels for various battery sizes. Further insights into this analysis are discussed in Sections 5 and 6. As shown in Table 1, AA alkaline batteries are the most common size in the set of batteries, that account for 56.3 % of the total. The distribution of samples per size is consistent with the literature (Kalmykova et al., 2017), with the AA type leading the battery market, followed by the AAA type.

5. Battery assessment: voltage and resistance analysis

To assess the reusability of the collected batteries, we measure their technical characteristics, including loaded-battery voltage and internal resistance. The loaded-battery voltage, often referred to as the load voltage, is the voltage in a battery's terminals when it is connected to an external load or circuit. On the other hand, the open-circuit voltage of a battery demonstrates the voltage measured in the terminals of a battery when it is disconnected from any external load or circuit. In simpler terms, it is the voltage generated by the battery in the absence of any current flowing through it. This property is also called the no-load voltage. Distinct from the open-circuit voltage, the loaded-battery

Table 1
The number (percentage) of battery samples per chemical/size group.

Size	Chemical							Total
	Alkaline	ZnC	Li	NiCd	NiMH	Pb	$ZnCl_2$	
9V	16 (1.6 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	13 (1.3 %)	0 (0.0 %)	29 (2.9 %)
A23	1 (0.1 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	1 (0.1 %)
AA	575 (56.3 %)	1 (0.1 %)	93 (9.1 %)	1 (0.1 %)	11 (1.1 %)	22 (2.2 %)	3 (0.3 %)	707 (69.1 %)
AAA	154 (15.1 %)	5 (0.5 %)	0 (0.0 %)	16 (1.6 %)	2 (0.2 %)	14 (1.4 %)	0 (0.0 %)	191 (18.7 %)
C	25 (2.4 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	25 (2.4 %)
D	68 (6.7 %)	1 (0.1 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	0 (0.0 %)	69 (6.8 %)
Total	839 (82.2 %)	7 (0.7 %)	93 (9.1 %)	17 (1.7 %)	13 (1.3 %)	49 (4.8 %)	3 (0.3 %)	1021 (100 %)

voltage considers the voltage drop that occurs when the battery is actively supplying current to power a device or perform work. The internal resistance of a battery quantifies its resistance to the flow of electric current within the battery. This resistance occurs from the impedance encountered by charged particles (ions) as they move within the battery's electrolyte and its internal components. The internal resistance results in a voltage drop in a battery, which is the difference between the open-circuit and loaded-battery voltages.

To determine the open-circuit and loaded-battery voltages, as well as the internal resistance of the batteries, we use a battery impedance tester, a load resistor, and a digital multimeter. First, a battery is connected to the battery impedance tester to measure its open-circuit voltage, which shows the voltage without any current draw. Following this, we connect the load resistor in the battery terminals to impose a load and replicate typical operating conditions. Utilizing the digital multimeter, we gauge the voltage in the battery terminals under this loaded state. By comparing this loaded voltage with the open-circuit voltage, we evaluate the battery's voltage under load. Finally, we use the battery impedance tester to determine the internal resistance of the battery.

To estimate the energy left in non-rechargeable batteries, we place particular emphasis on alkaline batteries, as they constitute the predominant type within our battery collection (comprising 82.2 % according to Table 1). Our inventory lacks a sufficient quantity of each battery type to perform a rigorous analysis. For instance, we only possess a single A23 alkaline battery. From this point onward, when referring to "battery types", we are specifically addressing AA, AAA, C, D, and 9-V alkaline batteries.

A comparison of physical data for various sizes of alkaline batteries highlights differences in capacity, energy density, and dimensions. AA batteries, offering capacities from 1800 to 2700 mAh and measuring about 50.5 mm by 14.5 mm, are versatile and commonly used in everyday devices. On the other hand, AAA batteries are smaller, at approximately 44.5 mm by 10.5 mm, with capacities between 1000 and 1200 mAh, and are suitable for compact electronics. C batteries, which have capacities of 7000 to 8000 mAh and larger dimensions of 50 mm by 26.2 mm, are designed for high-drain applications such as large flashlights. D batteries, the largest at 61.5 mm by 33.2 mm and with capacities ranging from 12,000 to 18,000 mAh, are used in high-power devices. Finally, 9V batteries, with capacities of 500– 600 mAh and dimensions of 48.5 mm by 26.5 mm, are specifically designed for specialized equipment such as smoke detectors.

Before comparing the technical characteristics of different battery types, we investigate whether these characteristics significantly vary among different producers of the same battery type. Upon analyzing the data, we discover that approximately 80 % of the 485 batteries are produced by two major brands. Therefore, for each battery type, we conduct a Mann-Whitney *U* test to examine potential effects. We choose this test due to the non-normal distribution of the data. The tests reveal that there is no significant difference in loaded-battery voltages for Types AA, AAA, C, and D among different producers, as the *p*-values (0.269, 0.453, 0.696, and 0.367, respectively) are all higher than the critical value of 0.05. The only significant difference is identified for Type 9V (*p*-value = 0.0008), which could be attributed to the limited number of samples available for this type in our dataset. A similar outcome is observed for the internal battery resistance (*p*-values of 0.342, 0.339, 0.594, 0.217, and 0.05, respectively). Given the insignificant impact of the specific producer, we aggregate the data of brands for each type of alkaline battery. The box plots in Fig. 1 illustrate the distribution of loaded-battery voltage and internal resistance for the batteries.

Next, we use the Kruskal-Wallis test to assess the significance of differences in technical characteristics among AA, AAA, C, D, and 9V alkaline batteries, with a critical value of 0.05. The initial test, including all alkaline battery types, reveals a significant difference in the load voltage (*p*-value = 0.024), that shows at least one difference among the five battery types at a 5 % significance level. Therefore, we repeat the Kruskal-Wallis test to assess subgroups of batteries. The new results show no significant difference among AA, C, and D alkaline batteries (*p*-value = 0.152). The same conclusion is reached for the second subgroup consisting of AAA and 9V alkaline batteries (*p*-value = 0.365). We conduct similar analyses for the internal resistance of batteries. The null hypothesis is rejected in favor of the alternative hypothesis of at least one difference among the five battery types (*p*-value = 0.000). Upon repeating the test, no significant difference is found between the samples of AA, C, and D alkaline batteries (*p*-value = 0.152). Nevertheless, it appears that 9V alkaline batteries exhibit a significantly higher internal resistance compared to AAA batteries (*p*-value = 0.000).

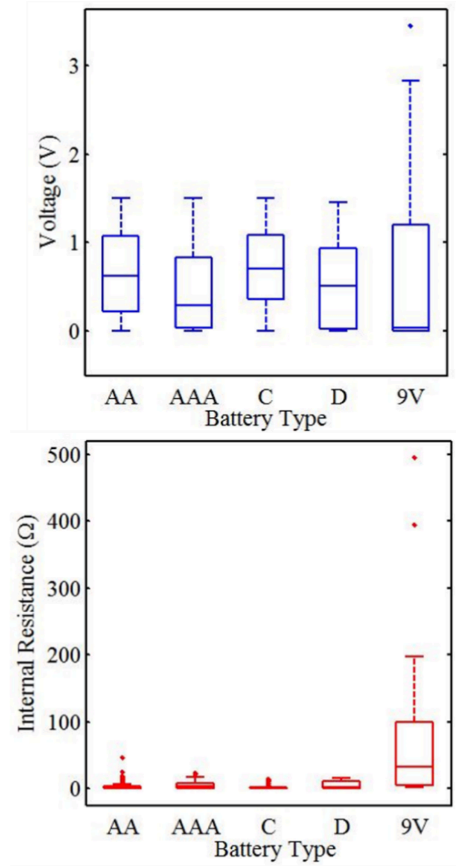

Fig. 1. The box plots display the central tendencies and variations in the loaded-battery voltage and internal resistance of AA, AAA, C, D, and 9 V alkaline batteries.

In the second step of data processing, we fit appropriate distributions to the technical characteristics data of battery samples. The Johnson's SB distribution, denoted as *J*, is identified as the best fit for the load voltage data based on the Kolmogorov-Smirnov test. The fitted distributions for AA, AAA, C, D, and 9V alkaline batteries are *J* (0.2, 0.58, 1.8, −0.13), *J* (0.56, 0.38, 1.57, −0.003), *J* (−0.001, 0.6, 1.77, −0.16), *J* (0.26, 0.53, 1.53, −0.13), and *J* (1.1148, 0.51019, 4.1765, −0.17972), respectively. The corresponding *p*-values are 0.07, 0.07, 0.98, 0.06, and 0.3 at the critical threshold of 0.05, which shows how well each distribution fits the data. It is important to note that Johnson's SB distribution is a versatile continuous distribution, useful for various phenomena. For the internal resistance of batteries, the Weibull distribution, denoted as *W*, is found to be the best fit. The fitted distributions for AA, AAA, C, D, and 9V alkaline batteries are *W* (0.56, 2.31), *W* (0.65, 3.93), *W* (0.68, 1.45), *W* (0.7, 3.64), and *W* (0.67, 51.68), respectively. The corresponding *p*-values are 0.4, 0.73, 0.06, 0.06, and 0.63 at the critical threshold of 0.05, indicating the goodness-of-fit of each distribution. Fig. 2 displays histograms and distributions of load voltage and internal

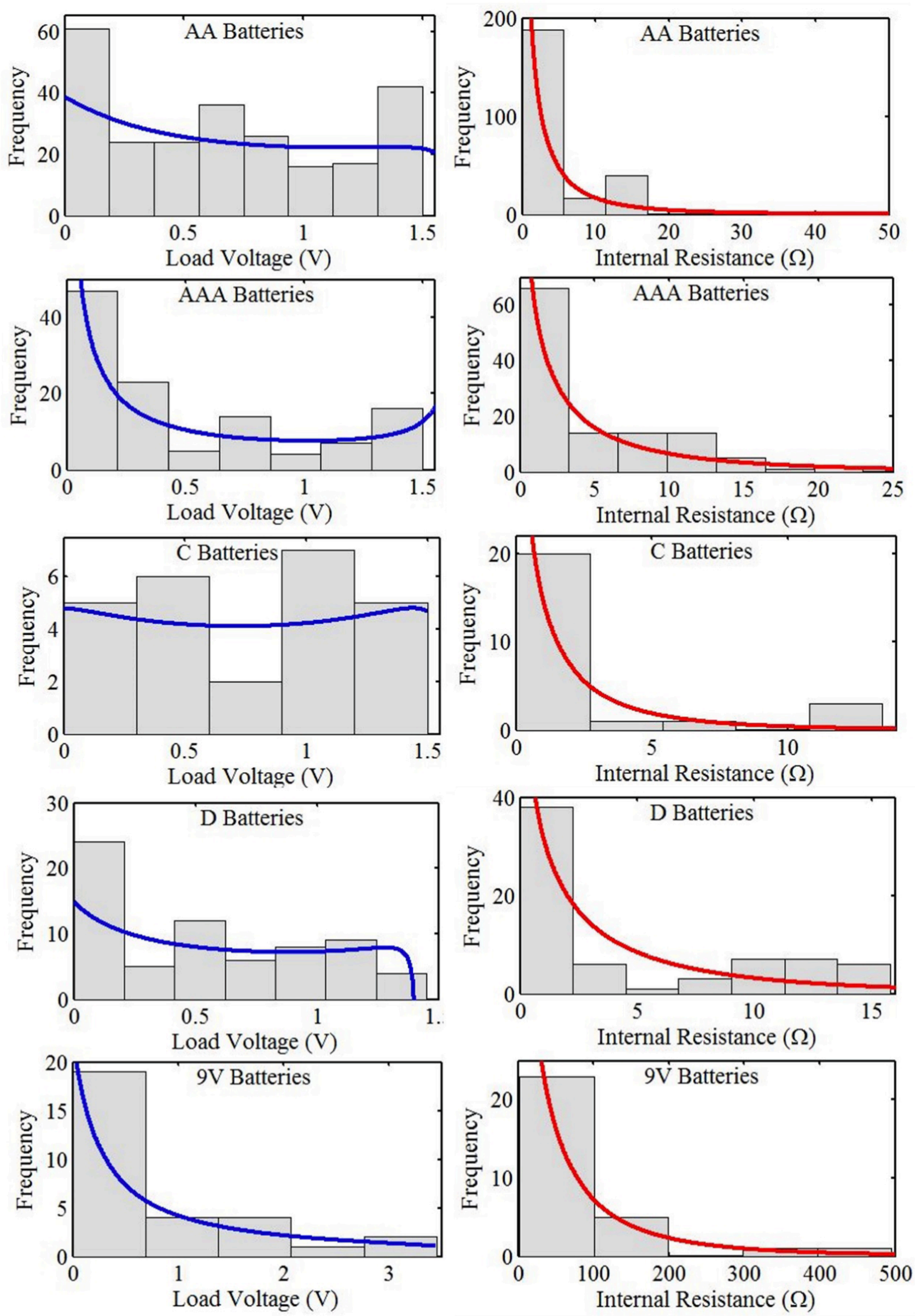

Fig. 2. Histograms and fitted distributions for the load voltages and internal resistance of AA, AAA, C, D, and 9 V alkaline batteries.

resistance for the batteries.

The Mann-Whitney *U* test showed that there are no significant differences in producer-specific variations for different types of alkaline batteries. Aggregating data by battery type and using the Kruskal-Wallis test revealed clearer comparisons of load voltage and internal resistance. 9V batteries had higher internal resistance than AAA batteries, indicating performance differences among battery types that should be explored further. Other methods such as Tukey's test, Bayesian analysis, and multivariate methods could provide additional insights, however, we chose not to use them due to various assumptions needed in those methods, and the sufficient robustness of our current results.

The load voltage data can be used to estimate the remaining service time of a used battery at a constant power rate. In Section 6, the relationship between the load voltage and the remaining service time is modeled using a logistic transformation function, which estimates the remaining service hours based on the load voltage. Parameters of the function are estimated to describe the shape of this relationship. This transformation converts the load voltage into the remaining service time, which represents the estimated remaining service hours. The logistic transformation is chosen for its flexibility and interpretability to capture the nonlinear relationship between load voltage and remaining service time.

Furthermore, the power law distribution is found to be the best fit for the remaining service time data. This implies that the distribution of the remaining service time is characterized by heavy-tailed behavior, where smaller values of the remaining service time are more likely compared to a standard exponential or normal distribution. The power law distribution is suitable for describing the variability in remaining service time for different conditions of load voltage. In the next section, we demonstrate how to use the findings from this section to estimate the remaining service time and remaining energy in the used batteries in detail.

6. Energy loss estimation model

A research question is to analyze the amount of energy remained in the collected used batteries and their reusability. To answer this question, we utilize technical life cycle data provided by one of the major brands.[1] The datapoints marked with symbols in Fig. 3 represent the remaining service time (hours) of an AA alkaline battery, determined by its load voltage, for constant powers ranging from 5 mW to 200 mW. For instance, if the current load voltage of a battery is 1.2 V, it can sustain a power output of 5 mW for approximately 200 h, whereas it can maintain a power output of 10 mW for about 100 h.

To illustrate how our proposed method can estimate the remaining energy in a used battery, we select AA alkaline batteries as a case study. Although the analysis mainly focuses on size AA batteries due to their widespread use, a similar analysis can be applied to other battery types. The producer provides additional information about the relationship between the load voltage and the remaining service hours in Fig. 3. Other than data provided by specific producers, to the best of our knowledge, there is no universally established formula that represents the relationship between the load voltage of a used alkaline battery and its remaining service time or charge. For rechargeable batteries, Peukert's Law is an empirical relationship that describes how battery capacity varies with its discharge current. Recent research (Dai et al., 2023) has verified its applicability to primary batteries. However, applying Peukert's Law to primary batteries requires conducting experiments to estimate its constant parameters, which is beyond the scope of our study. We link the load voltage data from Fig. 2 to the remaining service time in Fig. 3, by using appropriate transformation functions and fitting them to the datapoints presented in Fig. 3.

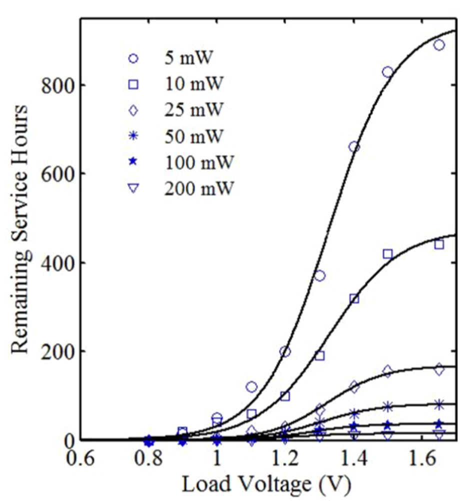

Fig. 3. The chart illustrates the remaining service time (in hours) of an AA alkaline battery in relation to its load voltage (in volts) for a range of constant powers(.
Source: Duracell Inc., 2017)

The variation in the remaining service time in Fig. 3 is well described by a logistic function, with high coefficients of determination (R^2 = 0.996, 0.993, 0.996, 0.999, 0.993, and 0.998). The logistic function model accurately represents the sigmoid growth profile (Ríos-Ocampo and Gary, 2022). The general form of this logistic function is defined as follows:

$$S = \frac{a}{1 + be^{cV}}, \tag{1}$$

Where S shows the remaining service time (hours), and V presents the load voltage, while a, b, and c are the three parameters defining the logistic function. The specific values of these parameters for the fitted functions presented in Fig. 3 can be found in Table 2. A nonlinear regression technique, known as the Levenberg-Marquardt algorithm, is used to estimate the parameters of the logistic function model from a dataset consisting of 10 data points. Using MATLAB, the model is fitted to the observed data points, adjusting the parameters to minimize the difference between the predicted and observed values. The process optimizes the parameters to best describe the data.

Fig. 4 provides histograms and fitted distributions (f_S) of the remaining service time for constant powers of 5 mW, 10 mW, and 25 mW. The power law distribution appears to be the most suitable statistical distribution for the data, with p-values of 0.14, 0.15, and 0.06 at the critical threshold of 0.05. A power law distribution represents a probability distribution where the likelihood of an outcome is inversely related to its magnitude, following a power law relationship.

By using the fitted distributions, we compute the survival probability (Kalbfleisch and Prentice, 2011), denoted as SP, which shows the probability that a used AA battery can be reused beyond a specified time s'. This probability is expressed as follows:

$$SP = Pr(S \geq s') = \int_{s'}^{a} f_S(s)ds, \tag{2}$$

Where a represents the parameter obtained from the fitted logistic functions in Table 2. Fig. 5 (a) illustrates this probability for constant powers of 5 mW, 10 mW, and 25 mW. For the sake of comparison, the probability that a used AA alkaline battery can be reused in a 5-mW device for at least 200 h is about 0.2. However, this probability becomes zero for a 25-mW device. The mean remaining service time for this battery is 108.3 h, 54.2 h, and 17.5 h for 5 mW, 10 mW, and 25 mW devices, respectively.

Next, the energy left in the batteries, denoted as E, can be computed by multiplying the constant power consumption rate, denoted as P, by

Table 2
The estimated parameters for the logistic functions fitted to the data of remaining service hours versus the load voltage.

Power (mW)	Parameters		
	a	b	c
5	942.48	828,798	−10.28
10	474.23	383,634	−9.68
25	167.62	5,802,430	−11.78
50	81.71	3,702,320	−11.59
100	36.32	15,340,500	−12.99
200	14.67	11,784,800	−13.27

[1] Technical Bulletins: https://www.duracell.com/en-us/techlibrary/technical-bulletins/.

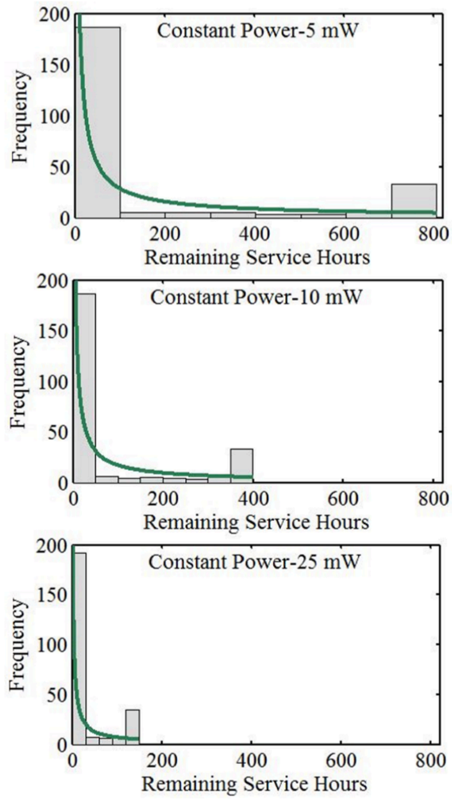

Fig. 4. These figures display histograms and the fitted distributions representing the remaining service time of an AA alkaline battery for constant powers of 5 mW, 10 mW, and 25 mW.

the remaining service time, shown as S (Hambley, 2018):

$$E = P \times S, \tag{3}$$

As a result, the unit of energy loss is measured in watt-hours. In Fig. 5 (b), we present the probability that the energy loss exceeds a specified value, denoted as e'. It is important to mention that the energy loss calculations are based on a constant power consumption of 5 mW per hour. However, it is worth noting that the results will not differ if other rates are employed. Equation (4) defines the energy-loss probability, denoted as EP. In this formula, f_E represents the distribution of the remaining energy, as obtained directly from Equation (3):

$$EP = Pr(E \geq e') = \int_{e'}^{a'} f_E(e)ds, \tag{4}$$

Where a' indicates the maximum energy capacity in a battery, which is equal to the product of the maximum service hours, denoted as a, and the constant power rate, denoted as P.

Based on Fig. 5 (b), the average energy left for a used AA alkaline battery is 0.54 Wh, approximately 13 % of its total energy. This represents the expected energy loss incurred if the used battery is not reused after the first life cycle. It is worth noting that improving the accuracy of remaining energy estimates will benefit from expanding the dataset to include a broader range of battery types and brands. In addition, future research should employ advanced techniques such as Bayesian updating and machine learning algorithms to increase prediction accuracy and better capture data patterns.

7. Impact analysis: findings and results

The disposal of approximately 2.11 billion single-use batteries annually in the U.S., as estimated in the introduction section, emphasizes the significant scale of the issue. In our battery samples, Type AA alkaline batteries constitute 57.9 % of all single-use batteries, that shows the consumption of about 1.22 billion AA alkaline batteries each year. While we acknowledge the limitations of our relatively small sample size and its collection from different locations within a specific state, we extrapolate the findings of this study to the U.S. market to provide an estimation. We need to mention a few points about our dataset. First, the distribution of samples per battery size aligns with existing literature (Kalmykova et al., 2017). Second, the batteries are collected from various locations with the aim of representing the market from diverse demographics and socio-economic factors as much as possible, given the point that there is no integrated system for collecting batteries from different regions in the U.S. In the following, we analyze the total energy, economic impact, and environmental impact from the imperfect utilization of AA alkaline batteries in the U.S. We also acknowledge the issue of extrapolating data to the national level and calculate the impacts specifically for the region from which the data are collected.

7.1. Total energy impact

The average per-unit energy loss is calculated at 0.54 Wh. Therefore,

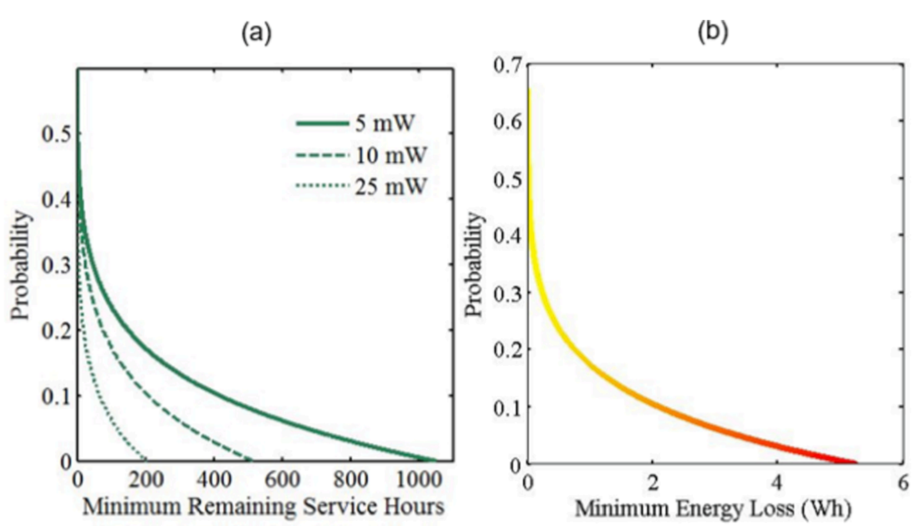

Fig. 5. (a) Survival probability (SP) of an AA alkaline battery at constant powers: 5 mW, 10 mW, and 25 mW. (b) Probability that the remaining energy in an AA alkaline battery (EP) exceeds a specified value based on a constant power consumption of 5 mW per hour.

the total energy loss amounts to approximately 660 MWh in the U.S. Taking into account the other types of single-use batteries, the overall energy loss is significant. For the State of New York, where the data were collected, the energy loss is approximately 40 MWh, given a total population of 19.70 million.

As we study energy utilization, addressing and minimizing these losses is an important step towards building a more sustainable and resilient energy infrastructure for the future. The average daily electricity consumption for a standard U.S. household is estimated at about 30 kWh. Therefore, 660 MWh of electrical energy could sustain the energy needs of about 22,000 U.S. households for a single day. Similarly, 40 MWh of energy loss in New York could meet the energy needs of approximately 1333 households for a single day. While this energy loss may appear relatively small for the U.S. economy, it becomes significant when considering all types of batteries. Moreover, the energy consumed during the recycling process is directly proportional to the quantity of waste batteries generated. Thus, any increase in the volume of waste batteries due to inefficient consumption practices would increase the energy demand for recycling.

7.2. Total economic impact

The per-unit energy loss for AA alkaline batteries stands at about 13 %. Consumers pay the full price for a battery, but they do not fully utilize its capacity. The per-unit price of AA alkaline batteries is approximately US$0.50, might seem relatively low on an individual basis. However, when scaled up to the collective consumption patterns, consumers end up wasting approximately US$80 million per year. For the State of New York, this translates to a waste of approximately $4.8 million per year. The underutilization of batteries can lead to additional economic concerns. The collection of spent batteries is a costly process, and recycling batteries carries its own costs. Therefore, any unnecessary increase in battery consumption worsens economic issues. This results in a financial loss for individuals and has broader implications for the environment. The discarded batteries contribute to electronic waste, and create challenges for proper disposal and recycling. In addition, improper recycling or landfilling of used batteries can lead to severe health issues.

Future research should address the economic challenges faced by waste management systems due to underutilized batteries. This includes conducting a thorough assessment of the costs associated with managing these batteries and analyzing their broader economic impacts on waste management infrastructure.

7.3. Total environmental impact

In this study, we seek to account for the environmental impacts of alkaline battery consumption in their entire life cycle. Typically, the life cycle impact of batteries remains constant unless there are changes in production technology or EoL/U recovery strategies. Previous research, such as a life cycle assessment study by Olivetti et al. (2011), quantifies the life cycle impact of alkaline batteries, including stages such as production and EoL recovery, using five key categories: Cumulative Energy Demand (CED), Global Warming Potential (GWP), Human Health, Ecosystem Quality, and Resources. The estimated values of these five categories per 1 kg of alkaline batteries are reported as 68 Mj, 4.3 kg CO_2 equivalent, 0.000012 DALY, 2.1 PDF*m^2yr, and 4.9 Mj surplus, respectively. In this study, we adopt a functional unit of 1 kg of alkaline batteries that are fully utilized by a consumer. We also consider a cradle-to-grave time horizon, which includes production, usage, and disposal/recycling phases.

While valuable, the above-mentioned estimated values by the literature should be adjusted to account for the impact of battery underutilization during their usage phase. Our analysis of discarded batteries reveals the imperfect utilization of batteries, which can result in an increased consumption rate of batteries by consumers. The estimated values for the five categories should be adjusted to incorporate the impact of imperfect battery utilization. To address it, we use data on remaining service hours. This is equivalent to the remaining energy inside the batteries, which is a battery utilization indicator for each individual consumer. For example, if it is estimated that 20 % of the nominal energy inside a battery remains unused, this implies that the battery owner has used only 80 % of the available energy. Therefore, this consumer would need to purchase alkaline batteries 1.25 times more often than in the case of perfect utilization to meet their battery demand. In this case, the consumer fully utilizes four out of five batteries in long term on average. Therefore, the life cycle impact associated with 1 kg of fully utilized batteries should be multiplied by 1.25 to account for the impact of underutilization for this consumer.

We hypothesize that underutilization of batteries might occur in two different ways: (1) the first group of consumers would not be willing to underutilize batteries, however they could not find secondary applications for the remaining energy due to improper design; and (2) the second group of consumers would not necessarily need the full energy inside batteries, but they often purchase battery packs that might not be completely utilized. Therefore, new batteries might be discarded along with partially used ones.

In Fig. 6, we present the adjusted life cycle impact values per 1 kg of alkaline batteries, along with 95 % confidence intervals to account for uncertainty in batteries utilization patterns. To determine these confidence intervals, we follow three steps: (1) we use the remaining service time data from Section 6; (2) the estimated energy left inside each battery is divided by its nominal energy, which results in the estimated utilization indicator; and (3) finally, the estimated utilization indicator is multiplied by the life cycle impact values from Olivetti et al. (2011) to derive the adjusted life cycle impact values. The range of adjusted life cycle impact is presented by confidence intervals for five impact categories.

In summary, the adjusted life cycle impact provides new questions for future research: How can manufacturers facilitate consumer utilization of their products? How responsibly do consumers use available resources? And how should manufacturers design batteries to minimize resource wastage? To examine the underutilization of resources, a more detailed analysis is required to determine the respective contributions of consumers and manufacturers.

8. Discussion and recovery solutions

The used AA alkaline batteries can be categorized into three primary groups based on the results of Section 6. The 246 AA alkaline batteries in our dataset can be categorized into three groups based on their remaining energy. The first group consists of 187 batteries (approximately 76 % of all AA batteries) that have minimal energy left, capable of supplying less than 100 h of constant power at 5 mW, as shown in the first plot of Fig. 4. The second group includes 18 batteries (7.3 %) with a remaining service time ranging from 100 to 400 h at a constant power of 5 mW. The third group comprises 41 batteries (16.7 %) with the highest energy levels, with a remaining service time of over 400 h at a constant power of 5 mW.

The first group, with the highest frequency (76 %), predominantly contains nearly depleted batteries. These batteries retain such a low amount of energy that it is impractical for a single used battery to be repurposed for common electronic devices. While using multiple batteries together may seem a preferable solution to reduce energy loss, it may not be practical at the household level due to technical challenges and limitations. In addition, non-technical users may require assistance in connecting used batteries to make use of their remaining useful life. Moreover, households typically have a limited number of batteries, which prevents the total remaining energy from being considered for reuse.

To improve the recovery strategy for this group of batteries, future research is recommended on improving collection methods for recycling. Exploring decentralized collection within communities could be a

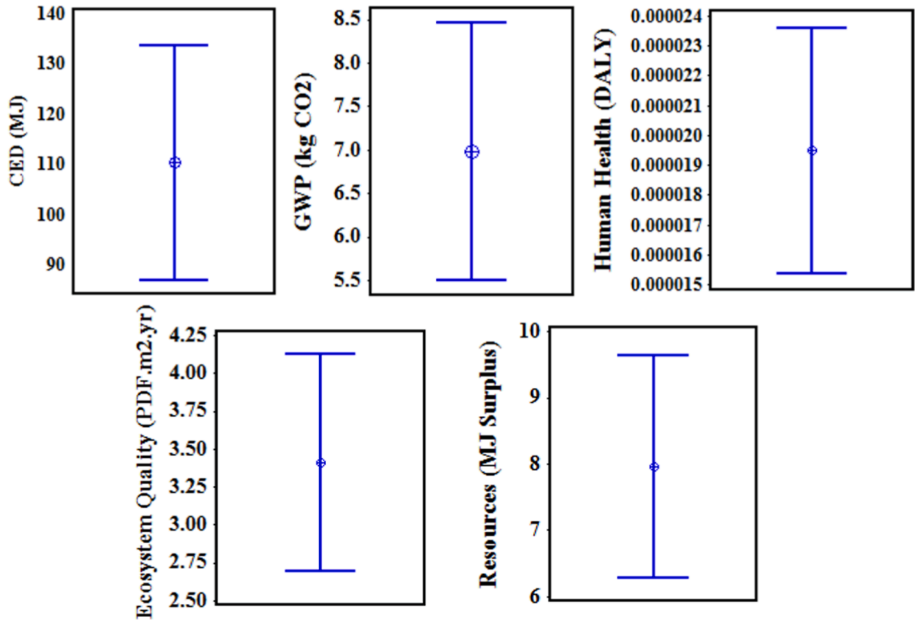

Fig. 6. The 95 % confidence intervals show the adjusted life cycle impact per 1 kg of fully utilized alkaline batteries considering the batteries utilization patterns.

viable approach. By dispersing collection facilities, consumers may be motivated to return fully depleted batteries. Research can explore logistical, behavioral, and environmental aspects to inform more sustainable recycling practices.

Batteries in the second group are less common (7.3 %), yet they possess a considerable amount of energy suitable for devices with lower power consumption, such as wall clocks. We hypothesize that consumers may mistakenly perceive these batteries as weak due to the absence of indicators displaying their health status. This misconception might arise, particularly when multiple batteries are used to meet voltage and power requirements, which leads to decisions based on the weakest battery. Further behavioral research is needed to validate this hypothesis. In addition, future studies could explore providing a cascaded utilization guideline to increase consumer awareness of battery consumption. This guideline could be a structured recommendation outlining the sequential allocation and usage of battery energy across multiple devices based on their energy requirements.

The third group contains batteries that are nearly new and more common than the second group (16.7 %). The reasons for consumers discarding these batteries are unclear, but it might be due to the absence of a gauge to display the remaining energy. While some rechargeable batteries have built-in indicators, disposable batteries often lack a feature that allows users to monitor how much energy is left. In addition, disposable batteries are readily available at affordable prices. This might make consumers less sensitive to efficient battery consumption. The implementation of public awareness campaigns for educating consumers on the environmental and economic benefits of extending the lifespan of batteries before disposal, may alleviate this issue.

While our analyses focus on single-use alkaline batteries, these methods can be extended to other battery types, including rechargeable ones. Extending the analysis to household rechargeable batteries necessitate revising the methodology to estimate their reusability, considering factors like the remaining number of charge–discharge cycles and full charge capacity.

Future solutions are needed to facilitate the full utilization of energy within batteries. These solutions should include a combination of technical improvements and consumer awareness initiatives. For example, batteries can be sequentially used in a set of devices based on their remaining energy, and this voltage-dependent consumption information can be included on labels. In addition, developing a smart battery tester with the ability to intelligently measure the remaining energy in batteries is worth investigating. Furthermore, it is possible to design technologies that facilitate the extraction of residual energy from partially depleted batteries. This needs energy harvesting devices for capturing and storing the remaining energy, and making it accessible for use in low-power applications.

In conclusion, promoting sustainable battery consumption practices need several actions. Raising awareness about the remaining energy in moderately used batteries is important to avoid their early disposal. Public campaigns should also focus on the benefits of prolonging the use of nearly new batteries. Innovations such as smart battery testers, energy recovery technologies, and clear labeling can help maximize battery efficiency. Furthermore, implementing community-based battery exchange programs and creating convenient drop-off locations can facilitate collection efforts and reduce waste.

9. Conclusion

In this paper, we assess a set of household-used batteries with the objective of exploring consumers' usage behavior. We measure the technical characteristics of these batteries to quantify the amount of remaining energy. In addition, we discuss the environmental and economic impact of energy loss in batteries. The findings show that the energy loss per unit for AA alkaline batteries is approximately 13 %, resulting in an annual energy loss of 660 MWh in the U.S. While an individual AA alkaline battery may cost around US$0.50, inefficient utilization across the U.S. results in an annual waste of approximately US $80 million. The EoL/U alkaline batteries are classified into three main categories: nearly depleted, partially spent, and nearly new, with suggested recovery solutions provided for each group. The main aspect of this study is quantifying the energy loss from underutilized single-use alkaline batteries. This shows the need for improved battery designs, recycling processes, as well as informing policies to reduce waste.

This study has several implications for policymakers, industry stakeholders, and consumers. For policymakers, it illustrates the need to improve recycling and collection infrastructure, potentially through decentralized collection points within communities to increase battery recovery rates. Industry stakeholders can utilize the findings to develop innovative technologies, such as smart usage indicators and easy-to-dismantle designs, to optimize battery usage and improve disposal practices. Finally, consumers could benefit from increased awareness about proper battery usage and disposal practices through public education campaigns.

We acknowledge certain limitations in this study. Our conclusions regarding energy loss and its associated impacts are based on a dataset from a specific geographical region and may not be directly applied to other regions characterized by different consumption patterns, pricing structures, or recycling systems. The majority of our samples were collected from New York State, which may introduce regional biases that affect the generalizability of our findings. Regional differences in usage patterns, environmental conditions, and recycling practices could impact the broader applicability of our conclusions. In the future, expanding the dataset to include batteries from additional states and regions, and collaborating with multiple facilities, is needed to better generalize the findings.

Furthermore, the calculation of energy loss and economic impact is based on certain assumptions and estimations, which may introduce uncertainties into the results. The study's reliance on manufacturer data for estimating remaining service hours and energy may not fully capture real-world usage patterns or EoL/U battery conditions.

Also, the study provides usage patterns for single-use alkaline batteries and their consequences for a specific timeframe but does not track changes over time. Future research should discuss potential trends or shifts in those patterns.

Also, future research should aim for a more geographically diverse sample and consider incorporating real-world usage data to improve the accuracy and relevance of the conclusions.

Also, further research is needed to conduct a thorough analysis that considers all related costs and benefits of battery recovery. This includes evaluating the economic feasibility of extracting the remaining energy relative to its value, as well as assessing the environmental impacts and societal considerations. Furthermore, the lack of an industrialized process to practically harvest energy from collected used batteries adds complexity to the feasibility of widespread energy recovery efforts.

Also, it is suggested to explore the impact of environmental factors such as temperature and humidity on battery performance. Assessing the rate at which single-use alkaline batteries lose charge when not in use can provide insights into their degradation and usability over time.

Future work will also incorporate more extensive real-world data and advanced predictive models to improve accuracy. Collaboration with manufacturers and gathering user feedback will be needed to refine estimations. Finally, we provide suggestions to improve battery utilization from an energy perspective. However, further technical research is needed to develop practical solutions for large-scale energy harvesting from alkaline batteries.

CRediT authorship contribution statement

Mostafa Sabbaghi: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sara Behdad:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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