To Refurbish or not to Refurbish? Towards an AI-based Evaluation System for Power Tool Batteries

Dominique Briechle, Marit Briechle-Mathiszig, Tobias Geger, Nelly Nyeck, Robert Werner
Institute for Software and Systems Engineering
University of Technology Clausthal
Clausthal-Zellerfeld, Germany
dominique.fabio.briechle@tu-clausthal.de; marit.elke.anke.mathiszig@tu-clausthal.de;
thomas.tobias.marcello.geger@tu-clausthal.de; nelly.nicaise.nyeck.mbialeu@tu-clausthal.de;
robert.werner@tu-clausthal.de

***Abstract*—The earth's resources are limited. Nevertheless, humans use more natural resources every year than the earth can provide. For that reason, sustainable usage of products is needed. Refurbishing processes offer an opportunity to extend the lifecycle of products like accumulators. For the refurbishing process, it is important for the operator to not only know the condition of the product but as well the possible expenditures it will cost to restore its functioning condition. The question whether it is possible to determine this kind of information about an accumulator from its external image has not yet been answered. Investigating this question can support the velocity of decision processes of whether a battery should be refurbished or given directly to recycling. This work describes the development of a refurbish and data collecting service and the design of a concept for adjunct data evaluation to investigate if Artificial Intelligence can draw a connection between the external features of an accumulator and the internal condition of the same. The preliminary results include the conception of the service as well as the derivation of assumptions based on the so far collected images of the batteries.**

***Index Terms*—Circular Economy, Recommendation, Digital Service Design, Product Lifecycle, Refurbishing, Artificial Neural Networks**

I. Introduction

The depletion of global resources is at an all-time high. Although the environmental impact of the currently conducted linear economy is drastically decreasing the quality of life in many countries, the broad expansion is a long time coming [1]. This can, however, be traced back to a few governing factors that are preventing the transition from the before-mentioned economic model toward a Circular Economy. Therefore, it is important to focus on those barriers, find solutions to remove them and support the transformation to a sustainable society. The main reason for the scarce repairing, refurbishing, and remanufacturing (3Rs) landscape in many countries is the monetary and time expenditure owners have to raise, which makes the continuation of product lifecycles difficult in comparison to the alternative of dumping the product and, in the best case, recycling its materials [2]. However, recycling quotas are still limited, and the resources which can be retracted are limited by the recycling plant installations and technical boundaries [3]. In terms of environmental sustainability, the 3Rs have an advantage in comparison with the production of a new good of the same make. We address the aforementioned obstacles, making 3R more attractive to both end users and service operators (e.g., companies that have the knowledge and capabilities to repair, refurbish, and remanufacture products) [4]. The conducted experiment therefore focused on two different thematic priorities: the first one is the design of the different aspects of a refurbishing process system, while the second one is the setup of a data recording pipeline that can catch the significant details of the specific power tool batteries to enable the development of Artificial Intelligence (AI)-based support tools. The present short paper aims to provide an overview of the refurbishing structure used for the restoring of the functioning conditions of the tool batteries, as well as the data foundation used for the further conduction of the battery assessment. The paper is therefore structured in section 2 in the Background and State of the Art section, followed in section 3 by the description of the initial Project Setup and the conduct of the project. This section is followed in section 4 by a review of the Preliminary Results. The paper closes in section 5 with a Conclusion regarding the usage of the recorded data in an AI-based support system to enhance end-user and operator knowledge.

II. Background and State of the Art

The development of the AI requires a understanding in both the domain-wise background and the technology-wise. Therefore this chapter is separated into two sub-chapters.

A. Domain Background

Fundamentally, repair entails restoring functionality to damaged or malfunctioning products, while refurbishment revitalizes products to nearly match their original state, thereby prolonging their lifespan [5]. In the context of the circular economy, repair and refurbishment are essential as they tackle the root causes of malfunctions, encourage the preservation of resources, and reduce the carbon footprint of producing new products. Although repair procedures are consistent with the concepts of sustainability, they encounter a significant obstacle due to the societal mindset of prioritizing convenience over sustainability, resulting in a preference for new products over refurbished ones [6]. To promote repair- and refurbishment-centric services, technological improvements, such as applying AI-based technologies in streamlining refurbishment systems, greatly contribute to improving their effectiveness and accessibility, as consumers' perceptions will be more inclined to repairing and acquiring refurbished products than buying brand-new ones. Expanding the market for repair services has a beneficial effect on the environment [7] in addition to having favorable economic effects for repair companies [8]. This is backed by current studies regarding the shortcomings of the current state of repair services and the suggestions to improve those with different measures, including up-scaling, better networking, usage of innovative technologies and governmental support [7]. However, additional thresholds are caused by user behavior. Laitala et al. are stating, that the willingness of the repair is highly dependent on the cost of a product, environmental concerns, initial cost and age of the product to name a few [18] Traditional repairs frequently cause uncertainty for consumers, raising concerns about reliability and efficiency. The proposed solution ensures repairability, reduces resource waste and saves time by providing a refurbished product upfront.

B. Technical State of the Art

Repair research is growing in popularity [5], thereby playing an important part in limiting environmental effects on the planet [9] via waste resource reduction. According to the findings of Sonego et al., [10], the literature review underscores that consumers encounter various barriers refraining from engaging in repair activities and the need to reduce them to achieve a circular economy. Highlighting these consumer-related obstacles goes in the same direction as emphasizing product lifespan extension through repair instead of discarding. Moreover, McLaren et al. [11] critically review circular economy literature and introduce four categorizations of repair: reconstruction/restoration, remediation, reconciliation, and reconfiguration [5]. This ongoing experiment could be categorized as reconstruction/restoration because the aim is to restore the product from its damaged state to its original function and purpose using standard materials to achieve an authentic refurbished product. Moreover, repair here might also be viewed as remediation, as long as the original purpose of the product is maintained and functionality is prioritized.

In order to derive a continuous function of the state of the battery based on image data or the expected expenditure for repair, we are dealing with a regression problem similar to that of human age or pose estimation [15]. For this task's general purpose, Convolutional Neural Networks (CNNs) like ResNet or VGG have proven to be applicable [15]. This area of research has made major progress on the topic of image classification over the last couple of years. For example, EfficientNetV2M (2021) [16] achieved an increase of 10 percentage points in accuracy compared to ResNet-50 (2015) with other recent models performing even better [17].

III. Project Setup

As mentioned in the Introduction, the project has two main goals: on the one hand, the first phase of the experiment contains the development of a structure that enables 3R operations and product-centered data recording and sets the foundation for the second phase of the experiment, the development of the AI-based expenditure assessment. This section includes a description of the first part of the experimental setup regarding the refurbishment system and the data recording and storage. The product chosen for the experimental conductivity of the system is a power tool battery, which is a widely used battery power system for a variety of different power tools. Therefore, clients can trade a refurbished accumulator, and in exchange, they send in their defective batteries of the same kind in order to stock them after restoring the functional condition of the product.

The described system, as shown in Figure 1, has two main **actors**, which interact with the system: On the demand side, we have our **client**, whose desire is to receive a functioning product. On the other side, we have our **operator**, who is responsible for the conduction of the recording and restoring operations in our system. The **first step** in our process flow contains the acceptance by the client of the previously generated offer from the operator. With the acceptance of the offer, the client agrees to pay a certain amount of money for the refurbishment service, while at the same time, the operator agrees to conduct the concluding operations. This leads to the **second step**, in which the operator sends the refurbished item together with a *Product Condition Survey (PCS)* to the client before he receives the defective product. The client therefore does not receive his battery in a restored condition back. He rather gets a product of the same kind, which is restored to a functional condition. In the **third step**, the client sends his defective battery with the filled-out *PCS* to the operator. The *PCS* contains questions regarding the type of defect and additional product life information and gives, on one side, the operator a short pre-assessment of the product's condition, on the other side it already gives a good insight into the kind of information a client is able to give the operator based on his own assessment abilities. Followed by the **fourth step**, the product is externally recorded by an *Automated Image Capturing Toolchain (AICT)*, which provides the foundation for the later aspired AI image assessment system. The *AICT* takes images from different angles of the product as well as an image of the product label to support the later-designed system with Optical Character Recognition (OCR). This enables the system, designed in the second phase, to receive additional information for certain products with an attached product label. In the case of our before-mentioned battery, this is for example the manufacturing location and date along with product line specifications. The **fifth step** contains the actual refurbishing operation, the conduction of additional product measurements,

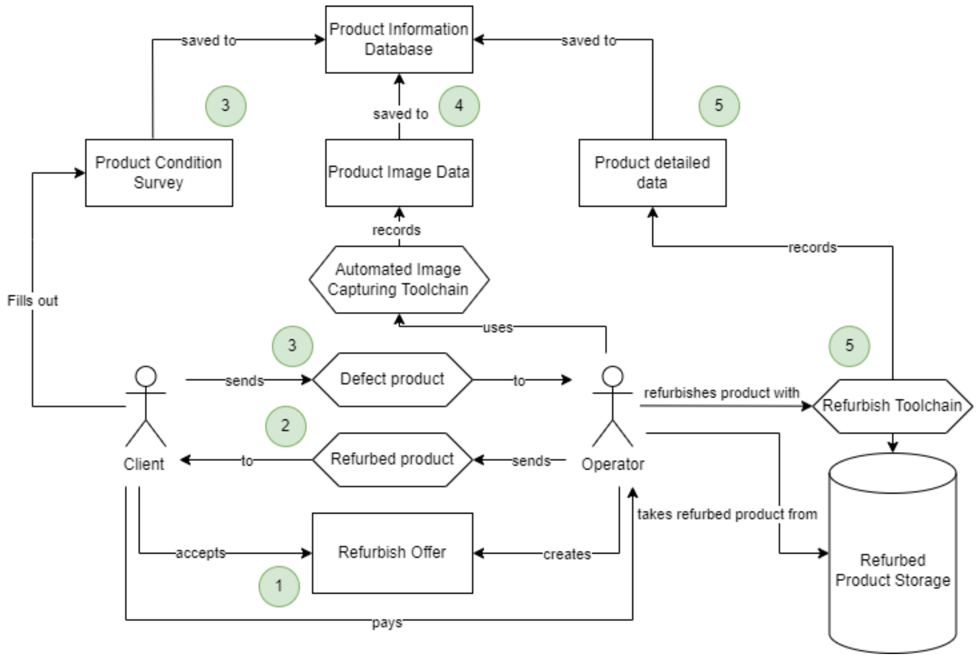

Fig. 1. Refurbishing structure for process conduction and data recording

and the storage of the refurbished product in the *Refurbished Product Storage*. The additional information about the product is in the case of the accumulator electrical data, for example, cell capacity, voltage, and current, as well as other repair data such as repair time and spare parts required. The experimental setup is highly modular and can therefore easily be retrofitted to suit other product type needs. Apart from that, the systems' modules can be uncoupled from their place in the system to be reassigned into another frame.

IV. Preliminary results

The preliminary results so far give a good overview of the applicability of both the overall concept as well as the results, which can be expected from the image collection unit. However, in order to determine the impact of such a system, further systemics regarding the logistic system as well as the financial backup regarding repair operations have to be evaluated and taken into account to refine the concept. On a technological level, the evaluation of suitable models and the training of the AI will be the next step of the project conduction. For this reason, images of the batteries were taken in a semi-automated way with the help of cooperative robots. In addition, the *PCS* sent to the user surveyed the estimated condition and usage scenario, among other information. In order to train for the cost of refurbishing operations, defects, and condition, the operator recorded the electrical information of the defective batteries as well as the resources required for restoration.

A. Image recording

To record the images for the future planned second phase of the experiment, the *AICT*, consisting of two co-bots of the same kind, is used to place the battery in a specific orientation. In the beginning, the battery is placed on a conveyor belt so that it can be transported automatically to the robot. The image-capturing device consists of two stereo cameras that enable the system to take pictures from a top-down and a 45° slanted perspective from the side of the belt. The first robot turns the battery 90 degrees around while the conveyor belt transports it back to the camera location where the cameras take an image of the battery. The process repeats after the battery is back in the *original* position. The other one grasps the battery from the side and places it facing the camera *above* the conveyor belt. This camera is used because the information on the product label can be used for OCR-based information extraction. At the end, the robot returns to the *handover* position and turns the battery 180° around on the top side. In total, 17 different views of each of the batteries are taken via both cameras: eight from each side where the battery is on top, eight where it is turned around, and one with a close up view of the battery label. To make sure that pictures are taken at the same position and angle, a script is written that takes the images automatically and switches between the two camera ports. Besides that, the use of co-bots gives the advantage that the images for all batteries are taken in the exact same position.

B. Battery Status

Preliminary results show that there are two main reasons for battery failure: Deep discharge with batteries in good condition or degraded cells with low remaining capacity, sometimes combined with a deep discharge. The latter is more often the case with 90% versus 10%. Interestingly, it is quite easy to detect deeply discharged cells as a user, however, it remains to be seen, whether the condition can be gauged as well. This would be highly beneficial, since refurbishing an accumulator with deeply discharged cells in good condition requires no repairing material and little time. We noticed that the quality of the battery depends on the type and the manufacturer of the cells. This is not apparent from the outside, but could be derived from the production year and number as well as design changes like the choice of colors and logos over different periods of time, like displayed in Figure 2.

Fig. 2. Captured batteries of two different production batches

C. Future Research Agenda

Adjunct to the first phase of the experiment, which is currently running, the future phase will be concentrated on the usage of the acquired product data, specifically training a machine learning model to estimate the expenditure for refurbishing a specific product based on the product type and its condition. To conduct this part of the experiment, the batteries are labeled and indexed to connect the specific records (images, data readings, refurbish time, and monetary cost) to a specific battery. Furthermore, data from user *PCS* can be used to derive the state of the battery and the refurbishment cost. For this, a regression is applied to make predictions. We believe Deep Neural Networks (DNNs) regression to be better suited for this kind of prediction over regression analysis since we are dealing with noisy, unreliable data provided by the user. Further, we have many dimensions with no clear correlation apparent and lastly, we want to have multiple outputs to predict both the state of the battery as well as refurbishment cost [13]. Finally, we want to use mixed data for the neural net to combine both the image data as well as data from the *PCS*. The models' input consists both of numeric and categorical values from the *PCS*, as well as image data of the battery to be assessed. In addition, data from the product's label is captured via OCR and used as additional input parameters. This has previously been done in the context of housing price prediction [14].

It is therefore the goal of the research to find the correlation between the external product features, like geometric or color-based anomalies, and the internal state of the product and investigate if these can be coherently assigned to one another. The outcome will show if causality can be drawn between the different parameters, which would also open up the research for other product groups. Based on those findings, guidelines and regulations can be formed, which in turn could fuel product lifecycle prolonging even further. The regulations could in turn enable those services on a wider scale and increase the economic feasibility of such operations. Further results might be able to outline specific parameters of the products in order to derive specifications for lifecycle prolonging operations.

V. Conclusion

The paper showed how the experiment can pave the way to increase service generation in the area of the 3Rs and how it can help with the design of digitized support systems. The current stage of the experiment allowed a first review of a potential instance of the service system for power tool accumulators and the review of the so far acquired product recordings to plan and design the adjunct AI-based systems for the second project phase. However, the full potential and efficiency of such a service systems relies heavily on the kind of product, the information density of the product generated by the stakeholders, and the functionalities of the designed solution. The second phase of the experiment will further show how AI-based systems could be implemented in the service system and how such systems can help to assess and prepare the clients' products for the concluding steps. Future research in this area could be continued by applying the service system to other product branches while investigating the business models that can fuel a broad application to accelerate sustainable business fields.

Acknowledgment

This work was funded by the Federal State of Lower Saxony, Germany.

References

[1] J. Grafström and S. Aasma, "Breaking circular economy barriers, Journal of Cleaner Production", vol. 292, 2021.

[2] J. Kirchherr, L. Piscicelli, R. Bour, E. Kostense-Smit, J. Muller, A. Huibrechtse-Truijens, and M. Hekkert, "Barriers to the Circular Economy: Evidence From the European Union (EU)", Ecological Economics, vol. 150, p. 264-272, 2018.

[3] C. Hagelüken, M. Schmidt, L. Schebek, and C. Liedtke, "Opportunities and limits of recycling in the context of the circular economy: Framework conditions, requirements, and recommendations for action, position of the resource commison at the german environment agency (kru)", June 2023.

[4] G. D. A. Galvão, J. de Nadae, D. H. Clemente, G. Chinen, and M. M. de Carvalho, "Circular Economy: Overview of Barriers", Procedia CIRP, vol. 73, p. 79-85, 2018.

[5] M.Van Der Velden, E. Maitre-Ekern, and D. K. Wanja, The Role of Independent Repair in a Circular and Regenerative Economy. Circular Economy and Sustainability, pp.1-26, 2023.

[6] S. Svensson-Hoglund, J. D. Russell, and J. L. Richter, "A process approach to product repair from the perspective of the individual", Circular Economy and Sustainability, 3(3), pp.1327-1359, 2023.

[7] I. Güsser-Fachbach, G. Lechner, T. B. Ramos, M. Reimann, ”Repair service convenience in a circular economy: The perspective of customers and repair companies”, Journal of Cleaner Production, vol. 415, 2023.

[8] M. D. Bovea, V. Ibáñez-Forés, and V. Pérez-Belis, ”Repair vs. replacement: Selection of the best end-of-life scenario for small household electric and electronic equipment based on life cycle assessment”, Journal of environmental management, vol. 254, p.109679, 2020.

[9] W. Steffen, K. Richardson, J. Rockström, S.E. Cornell, I. Fetzer, E. M. Bennett, R. Biggs, S. R. Carpenter, W. De Vries, C. A. De Wit, and C. Folke, ”Planetary boundaries: Guiding human development on a changing planet”, Science, 347(6223), p.1259855, 2015.

[10] M. Sonego, M. E. S. Echeveste, H. G. and Debarba, ”Repair of electronic products: Consumer practices and institutional initiatives”, Sustainable Production and Consumption, 30, pp.556-565, 2022.

[11] D. McLaren, J. Niskanen, J. and Anshelm, ”Reconfiguring repair: Contested politics and values of repair challenge instrumental discourses found in circular economies literature”, Resources, Conservation ‘I&’ Recycling: X, vol. 8, p.100046, 2020.

[12] M. Young, ”The Technical Writer’s Handbook”, Mill Valley, CA: University Science, 1989.

[13] M. Imaizumi, and K. Fukumizu, ”Advantage of Deep Neural Networks for Estimating Functions with Singularity on Hypersurfaces”, Journal of Machine Learning Research, vol. 23, p. 1–53, 2020.

[14] E. H. Ahmed, and M. N. Moustafa, ”House price estimation from visual and textual features”, Computer Vision and Pattern Recognition, 2016.

[15] S. Lathuilière, P. Mesejo, X. Alameda-Pineda, and R. Horaud, ”A Comprehensive Analysis of Deep Regression”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, issue 9, p. 2065–2081, 2018.

[16] M. Tan, Q. v. and Le, ”EfficientNetV2: Smaller Models and Faster Training”, Proceedings of Machine Learning Research, vol. 139, p. 10096–10106, 2021.

[17] X. Yu, Y. Xue, L. Zhang, L. Wang, T. Liu, and D. Zhu, ”NoisyNN: Exploring the Influence of Information Entropy Change in Learning Systems”, 2023.

[18] K. Laitala, I. G. Klepp, V. Haugrønning, H. Throne-Holst, P. Strandbakken, ”Increasing repair of household appliances, mobile phones and clothing: Experiences from consumers and the repair industry”, Journal of Cleaner Production, vol. 282, 2021.