Artificial Intelligence in the Effective Battery Life Cycle

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The rapid growth of battery production and usage will cause waste and disposal-related issues as these batteries reach end-of-life. Moreover, it also causes the depletion of natural mineral resources. Thus, effective battery reuse and recycling procedures are highly important because they contain metals of critical importance. The recycling of batteries causes the return of valuable materials, including lead, lithium, nickel, cadmium, and copper, back to the value chain, partially easing the need to extract new resources. Moreover, recovering metals from batteries reduces the burden on landfills, the burden on the environment, and the negative impact on human health. The critical material's recirculation also leads to a reduction of the ecological CO_2 footprint, which is connected with battery cell production and may provide CO_2-neutral battery cell production. Improper battery waste disposal causes harmful effects on human and animal health, as well as the environment, as they contain a huge number of heavy metals. These waste compounds contaminate water, soil, and vegetation.

Keywords: battery waste ; waste management ; artificial intelligence ; genetic programming

1. Artificial Intelligence in Battery Production and Monitoring

Battery production is one of the components of sustainable development, including reduction, clean energy, and economic development. An important role in battery production is played by cost [1]. The chemical and physical characteristics of batteries can be estimated. Optimizing the battery manufacturing process is complex (multi-criteria) and costly. It includes the optimization of factors such as, for example, electrode and slurry formulation, choices of additives and solvents, time and speed of premixing powders and slurries, coating speed and comma spacing, and time and evaporation temperature. Here, methods based on Artificial Intelligence (AI), in particular, Machine Learning (ML), can significantly simplify this process and reduce its cost while they are operating on multidimensional data sets [2]. The first important issue is to collect a large amount of reliable data on which the algorithms can perform the optimization. Incorrect assumptions and unreliable data will lead to unreliable results. Some guidance on designing suitable AI-based methods is applied to estimate the state of battery charge [3][4] and predict the battery life cycle [5][6], or LIB electrode manufacturing [7].

The State of Charge (SOC) depends on several factors, such as temperature, ageing, cell unbalancing, hysteresis characteristics, self-discharge, and charge/discharge rate. It plays an important role in predicting EVs' driving race and optimal charge control, which are crucial in reducing the carbon footprint. It can be estimated using various methods based on Artificial Intelligence, but each disadvantage is the accuracy and availability of data. The estimation of SOC requires applying the algorithm to describe the battery's remaining capacity, which was described in the study [4]. In the paper [8], a simple deep neural network combined with a Kalman filter was used to estimate the SOC of the battery. In [9], the fuzzy logic methodology was used for this purpose, which analyzed the data coming from impedance spectroscopy and/or coulomb counting techniques. A genetic algorithm was used to evaluate the various types of batteries [10][11]. Genetic algorithms provide less estimation error (5 times smaller) compared to fuzzy logic ones. The support vector machine (SVM) was used to establish the relationship of the SOC to the Ni-MH battery's voltage, current, and temperature [12]. Thus, the paper [3] proposed a recurrent neural network (RNN) with long short-term memory (LSTM) for the estimation of SOC in the case of LIB. The algorithm was based on measured voltage, current, and temperature. In [13], the dependence on ambient temperatures is included. In turn, in the study [14], convolutional neural networks (CNN) and RNN were used to predict. This approach enables the prediction of SOC with a maximum mean average error under 1% and a maximum root mean square error under 2%, based on discharge profiles. It provides a reasonable estimation of nonlinear relationships between SOC and measurable variables. Recently, hybrid methodologies to estimate SOC were investigated in the study [15]. In work [16], an adaptive extended Kalman filter was proposed. Thus, hybrid techniques have the potential to multiply the advantages of individual components and thus enable a more accurate SOC estimation.

On the other hand, the study [5] shows that Machine Learning-based techniques can predict the battery life cycle with a 4.9 percent test error using the first five cycles, considering the evolution of the discharge voltage courage. In the paper

[17], the cognitive digital twin batteries' design and development were shown. This Artificial Intelligence-based digital creation enables research to optimize the entire life cycle of a battery. In [5], cycle life prediction models were proposed. As input data the cycle lives of batteries ranging from 150 to 2300 using 72 different fast-charging conditions have served. In research [7], Artificial Intelligence-based tools, in particular based on a decision tree, deep neural network, and SVM to predict correlations between LIB properties and manufacturing parameters, were proposed. It took into account the characteristics of the electrode, namely the active material mass loading and porosity. It turned out that SVM links high accuracy of prediction (above 90 percent) with the possibility of graphical analysis of the results. A huge effort has been made to understand and experimentally validate the batteries, which are working with constant current, voltage, and temperature, while there is still a gap in the case of the batteries, which are working in severe, hot, wet, and rainy conditions. Here, the surrogate battery models can be helpful, and they can be used as an input dataset to the battery optimization process [18]. Thus, Artificial Intelligence can help increase the sustainability of batteries.

Artificial Intelligence can also be applied as an effective tool for the analysis of the material characteristics of battery [19] and the LIB failure mode [20]. In the study [19], as a training set, public battery cycling data, which contains 124 $LiFePO_4$/graphite cells being cycled to end-of-life [16], was used. It turned out that to predict the battery properties with high accuracy, only single-cycle data are needed. The interesting solution for evaluating the residual energy of lithium-ion batteries (LIBs) based on Artificial Intelligence, in particular genetic programming, was presented in the paper [21]. The quantitative results determined the relationship between stress and capacity and can provide an optimized recycling strategy for batteries applied to electric vehicles, which is extremely important, while current generations of batteries link active materials with high energy densities with highly inflammable electrolytes.

2. Artificial Intelligence in Waste Management, Including Battery Waste Management Systems

Artificial Intelligence-based algorithms can solve various issues of information processing, including pattern recognition, classification, clustering, dimensionality reduction, image recognition, natural language processing, and predictive analysis. Recently, Artificial Intelligence was also applied in waste management [22][23], providing the opportunity to link waste management, joint supervision and collection process, and safety.

Another important issue in waste management is connected with the efficiency of the cleaning process, while Artificial Intelligence can also support waste collection schedules. The intelligent trash cans can send data, such as the presence and volume occupied by garbage, using the Internet. In the paper [24], a waste collection system based on location intelligence and applying graph optimization algorithms as a part of Smart City (Copenhagen, Denmark) was proposed. The proposed solution returns the data concerning trash level collected by the embedded sensors to the server over the Internet, which optimizes the collection routes and sends this information to workers. In this study, input data were: waste level of trashcans, which come from 3046 trashcans, and available open data about the city of Copenhagen, Denmark. On their basis, the optimal schedule of waste collection from individual places is determined, taking into account the optimization of the driving distance of the daily routes based on the Shortest Path Spanning Tree (SPST) to calculate the minimum driving distance between points and a genetic algorithm to predict the minimal driving distance between the points, is determined.

The identification, localization, and size determination of waste are based on image recognition techniques. In the study [25], based on images, the determination of the location and the degree of filling of the containers with the use of four Laws Masks and a set of support vector machine (SVM) classifiers with 99.8 percent accuracy was proposed. The containers were classified into three groups, i.e., empty, partially full, or full. The assignment to a particular group determined the garbage collection schedule. Input data were in the form of pictures of bins and the nearest neighborhoods (800 × 600 pixels), including 60 rotated and 160 unrotated. As a training set, unrotated pictures were used, while during testing of the solution proposed, both unrotated and rotated pictures were. All pictures were converted into grayscale and subjected to the automatic edge detection procedure. The bin position of the image was detected with Hough line detection and cross-correlation. It turned out that the algorithms proposed are robust against bin shift and rotation. In the research [26], the classification of electrical and electronic waste from trash pictures using the deep learning convolutional neural network (CNN) was presented. The proposed solution provides efficiency of 97 percent. As input data, pictures of refrigerators, washing machines, and television sets (three classes) in the RDG format (128 × 128 pixels) were taken. The training set includes 160 pictures (60 for each class), while the testing set includes 30 pictures (10 for each class). The pictures of waste are sent to the server, where they are subjected to the object recognition procedure. Once the waste is identified and located, waste collectors can plan for efficient collection. The systems can recognize three categories of e-waste, namely: refrigerators, washing machines, and monitors or TV sets. In the paper [27], convolutional neural networks were used to identify hazardous recyclable materials, such as batteries, syringes, and nonhazardous waste, with an accuracy of 90 percent. Datasets, including three categories (i.e., batteries, syringes, and nonhazardous waste), in the number of pictures taken in front of a white background with moderate lighting (512 × 384 pixels): 23, 91, and 1984, respectively. Artificial Intelligence-based algorithms are also involved in trash control in institutions, for example, universities [23]. This system combines linear regression (LR) with Machine Learning techniques. Dijkstra's algorithm optimizes the path for waste collection based on historical data. It operates on data containing information about the current state of filling the bin, i.e., the level of waste and bin position. The pictures were collected for 4 months during the academic year.

Thus, waste management can be treated as a multi-hierarchical clustering problem. In the paper [28], the concept of an AI-based classification of medical waste, e-waste, and toxic atmosphere pollutants, taking into account real-time indicator conditions such as daily waste and strain, was proposed. This system contains three modules: the input module (responsible for defining the essential trash characteristics), the second level module (description of the toxic patterns), and the community module. The general idea of the system is derived from LCA, MCA, and Extended Producer Responsibility. It enables e-waste tracking, taking into account the safety of the whole process. In the case of the application of Artificial Intelligence, this can reduce the duration of the assessment process by at least 35 percent.

Waste management, in particular solid waste, is an important issue, taking into account the negative impact on human health and the environment [29][30]. For an efficient waste management system, Artificial Intelligence has great potential [31]. According to the research analysis presented in [32][33][34], the reduction of waste through recycling helps to achieve a circular economy. The prediction of an accurate waste amount, mass, and type is crucial in waste management. Thus, in the paper [35], the convolution neural network was used to predict the waste mass. In the study [36], artificial neural networks and the Machine Learning framework (MLDPAF) were applied to the effective planning of waste management, including the prediction of waste amount and effectiveness of waste collection. The research [36] shows an attempt at waste management on an academic campus. In turn, in the paper [37], the concept of an effective construction waste management system was proposed.

Another issue connected with waste management strategies is waste amount prediction. In the study [38], multi-layer perceptron artificial neural networks (MLP-ANN) were used for the verification of annual waste production, including municipal, commercial, construction, and demolition waste. For the forecast, the data, which contain solid waste datasets deposited at Askar Landfill in Bahrain between 1997 and 2016, were used. It turned out that artificial neural networks enabled the estimation of the future-proof generation of different types of waste with high accuracy. In the paper [39], the comparison of different artificial neural networks, i.e., adaptive neuro-fuzzy inference systems, discrete wavelet theory artificial neural networks (DW-ANN), discrete wavelet theory–adaptive neuro-fuzzy inference systems (DWT-ANFIS), and genetic algorithms, for the amount of waste prediction has been made. This study covered two data streams, namely, data that come from governmental, semi-governmental, and private publications from the period of 1993–2011 and data that come from field surveys. It turned out that the most accurate forecast was delivered by a genetic algorithm. In the study [40], four options were used to estimate the ability of intelligent systems algorithms to predict monthly amounts of waste generated—support vector machines (SVM), adaptive neuro-fuzzy inference systems (ANFIS), artificial neural networks (ANN) and k-nearest neighbors (kNN). It has been shown that AI can be successfully used to estimate the amount of generated waste, and the best results were obtained for the ANFIS (most accurate peak forecasts) and kNN (monthly average waste prediction) systems. The medical waste generation rate was estimated in [41] based on multiple linear regression, artificial neural networks, fuzzy logic–artificial neural networks, support vector regression, least squares support vector regression, and fuzzy logic–support vector regression. It turned out that in the case of hospital solid waste, the higher accuracy was provided by fuzzy logic–support vector regression.

3. Artificial Intelligence in the Waste Sorting

Waste sorting, i.e., the process of separating waste into different types, plays a crucial role in the closed circular economy model [42]. The available sorting methods can be divided into two groups: manual sorting and automated/mechanical sorting, with the application of robotic technology or a combination of these two types [43]. In the case of solid waste, the manual approach prevails [44]. To provide an automatic waste sorting system based only on pictures of waste in [45], convolution neural networks and support vector machines were applied. The system classified waste into three groups, namely plastic, paper, and metal. It operates on colored images in png format (256 × 256 pixels). It turned out that support vector machines provided higher efficiency than convolution neural networks. An interesting approach was proposed in the paper [46], placing RFID tags on packages that would enable the identification and classification of individual plastic packages, for example, using Artificial Intelligence. The recycling robot ZRR2 from ZenRobotics in Finland [47] was the first attempt to apply such a solution in practice [48]. It has built-in computer vision and deep learning algorithms. The robot enables the automatic separation of selected waste from solid construction and demolition waste. In the study [49], the ZRR robot was applied to the sorting of municipal household waste streams. Herein, the main limitation in the application of the system is the protection of personal data from households. In turn, for the already collected waste the identification to sort them into two groups, i.e., glassware and plastics, based on a convolution neural network was proposed in the paper [50]. The input data was gathered with an RGB camera, i.e., 103 pictures of waste (50 glassware, 53 plastics). To increase the amount of data, image enhancement was done to the training set. After identification, the gripper sorting robot separated the waste into two groups. In the study [51], an Artificial Intelligence-based, especially hierarchical deep learning, algorithm was applied to waste detection and classification in food trays. As input, the Labeled Waste in the Wild dataset was used, which contains 1002 RGB pictures of used food trays (3456 × 4608 pixels) that have been taken with several different smartphones. Some of the objects shown in the photos were not wasted. These pictures were used to label the shape and material of the visible waste. In the paper [52], to distinguish nails and screws in construction waste, a region-based convolutional neural network was applied. The COVID-19 pandemic also revealed the need for automatic sorting of medical waste, including polyethene terephthalate (PET) waste from the pandemic period. In the study [53], the support vector machine with an accuracy of 96.5 percent was proposed for this purpose.

4. Artificial Intelligence in Battery Waste Recycling

Effective and environmentally friendly waste management is one of the biggest problems in the whole world. Waste processing and recovery are crucial elements in waste management systems [54][55]. One of the crucial parts of battery waste management is the recycling process [56]. Lithium-ion batteries can be recycled using various methods, including pyrometallurgical, hydrometallurgical, and biological recycling to recover valuable metals [57][58][59]. **Figure 1** shows a schematic diagram of the management system and waste recovery methods for the current batteries (including LiBs).

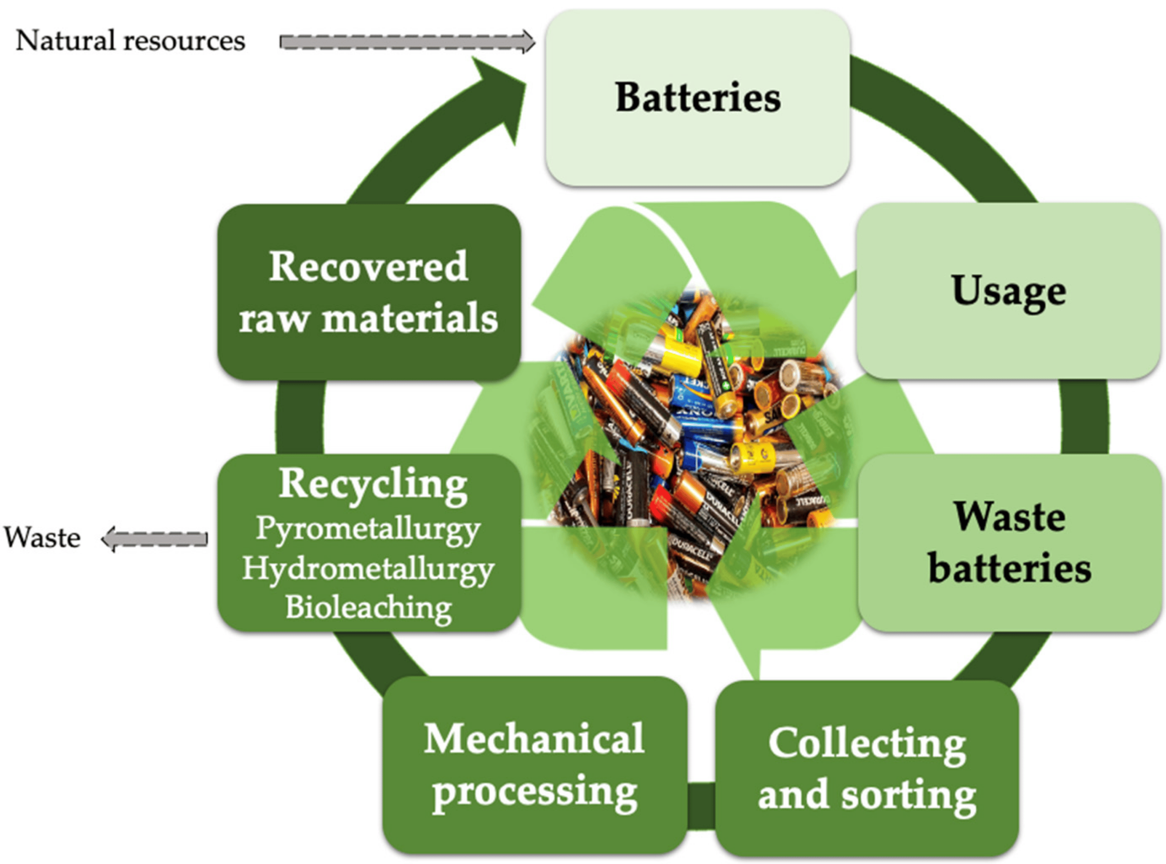

Figure 1. The closed-loop system in batteries and their waste management.

The pyrometallurgical approach is based on the high-temperature treatment of the battery waste in a wide range of temperatures in the furnace. During this process, the decomposition of organic materials occurs, and new alloys are formed [60]. It is an effective way to recover metals such as cobalt, nickel, and copper, while lithium, manganese, and aluminum get into slag or kiln dust. As a consequence, lithium, manganese, and aluminum can be extracted with a large financial outlay in another process. During this process, semi-finished products are produced, which, to be reusable, have to be subjected to further purification. The huge disadvantage of the pyrometallurgical process is the small number of recyclable materials and low efficiency in the case of low concentrations of recyclable materials [60][61]. The pyrometallurgical process is quite simple and does not cause any operational problems, but it causes air pollution and requires a lot of energy [62]. Moreover, there is no need for sorting or reduction of battery size [63][64]. Low energy consumption and high recycling efficiency are the hallmarks of hydrometallurgy processes [65]. Hydrometallurgical methods of recovering metals from used batteries most often mean acid leaching, which is based mainly on the application of strong inorganic acids and reduction. For example, refs. [66][67][68] proposed the application of sulphuric acid and hydrogen peroxide as leaching agents due to the fact that the use of strong inorganic reagents is associated with technological problems, such as corrosion and rapid destruction of equipment, the emission of toxic vapors, and the danger of working with strong chemicals, currently. The interest of scientists is focused on the possibility of applying organic acids (e.g., acetic, citric, and DL-malic acids) in the leaching process of spent batteries [69][70]. In addition, an up-and-coming alternative to the pyrometallurgical and hydrometallurgical recovery of metals from waste batteries is the bioleaching process using microorganisms such as bacteria and fungi [71][72]. Biological methods of metal recovery allow for the reduction of the formation of secondary pollutants (including no toxic gas emissions) and, at the same time, are characterized by high efficiency, safety, and the relatively low costs of the process. However, the duration of the reaction in most cases is longer than for the acid leaching with the use of chemical reagents [73][74].

Since the recycling of metals from battery waste is a complex task, its efficiency can be improved by the application of various prediction methods, including Artificial Intelligence [75]. In the paper [76], the Machine Learning approach, including linear regression, random forest regression, AdaBoost regression, gradient boosting regression, and XG boost regression, to optimize the metal recovery of Zn and Mn from battery waste was proposed. As input, data on energy substrate concentration, pH control of bioleaching media, incubating temperature, and pulp density were used. The maximum Zn and Mn yield was the output data. It turned out that XG boost regression provided the best estimation, while linear regression was the least accurate. While the lithium-ion batteries from electric vehicles cannot be directly reused, the development of effective sorting of cells is of high importance [77]. In the study [78], the screening method for retired battery packs was shown. The support vector machine, with an accuracy of 96.8 percent, was applied. The input data come from 12 retired batteries, i.e., 240 cells, and include their capacities and resistances. It turned out that the proposed approach can reduce the time needed for sorting and four-fifths, in comparison to the manual process. In the paper [79], the sorting methods of lithium-ion batteries in large quantities were described. The degradation state of the battery was determined with X-ray radiographic scanning and digital image contrast computation. The proposed approach provides an accuracy of 79 percent. In turn, in the study [80], the Artificial Intelligence-based sorting method was applied to the recycling of unused mobile phones. As a first step, the retired batteries from mobile phones were subjected to magnetic separation, eddy current, and pyrometallurgical and hydrometallurgical processes. Next, the pictures, which were taken with purified metal, were classified with the convolutional neural network with rectified linear unit (ReLU) activation function. To increase the amount of input data, image augmentation was used.

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