Knowledge Graph for Disassembly of Electric Vehicle Batteries

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Contributor: Jiangbiao Wang , Jun Huang , Ruiya Li

End-of-life (EoL) electric vehicle (EV) batteries are one of the main fountainheads for recycling rare metal elements like cobalt and lithium. Disassembly is the first step in carrying out a higher level of recycling and processing of EV batteries. EV battery knowledge graphs can provide detailed structural information to assist operators in understanding the layout and composition of batteries. Planning the disassembly sequence using knowledge graphs can facilitate the robotic disassembly of EV batteries.

electric vehicle battery | disassembly sequence planning | knowledge graph

1. Introduction

In 2012, Google Inc. originally proposed the concept of a knowledge graph in Google's Chrome browser search engine to provide users with better search experiences [1][2]. As structured semantic knowledge networks, knowledge graphs are gaining ever-increasing attention from industry, business, and academia, which offer relevant support for various scenarios, including intelligent search, technical support, and decision-making systems [3]. In addition, semantic web knowledge bases have been created and used, such as YAGO [4], FREEBASE [5], and DBpedia [6].

The recycling and reuse of EoL EV batteries have emerged as prominent approaches in recent years. The remanufacturing of EoL EV batteries has also gained recognition [7]. Human–robot collaborative disassembly and robotic disassembly of EoL EV batteries are more efficient and safer than traditional manual disassembly. The involvement of robots in disassembly operations can reduce time and save costs [8][9]. Human–robot collaborative disassembly has become a frontier by combining the advantages of robots and human operators [10].

An assembly information model based on a knowledge graph can facilitate the sharing of assembly process documentation information and increase the rate of information interaction during the development phase of the assembly process [11]. The advantage of EV battery knowledge graphs lies in the ability to display the first level, or even the second and third levels, of surrounding nodes intuitively on a graph. These surrounding nodes are connected to the starting node through relationships. EV battery knowledge graphs can provide detailed structural information to assist operators in understanding the layout and composition of batteries. In addition, planning the disassembly sequence using knowledge graphs can facilitate the robotic disassembly of EV batteries.

2. Processing Technical Levels of End-of-Life EV Batteries

Some scholars introduced the battery disassembly and recycling processes in terms of process improvements and technical levels. Pang Haifeng et al. [12] introduced the situation of lead–acid battery disassembly. The article pointed out that the disassembly and recycling technology level of lead–acid batteries is low, with high energy consumption and low metal recovery rates. Techniques referring to cleanliness, refinement, intelligence, and digitalization need to be improved. Disassembly equipment for the process of crushing and sorting EoL EV batteries was structured by Kang Fei et al. [13]. It improved the efficiency and digitalization of battery disassembly. Sonja Rosenberg et al. [14] explored how different disassembly steps affect EV battery disassembly time. The cost of a disassembly plant was also estimated. Due to the varying design architectures of EV batteries on the market, the condition and safety of these batteries during recycling remain uncertain.

The market is facing three major problems in EV battery disassembly and recycling [15]. Firstly, manufacturers produce batteries with various models and parameters. Secondly, in complicated disassembly tasks, the disassembly sequence becomes confusing, leading to low efficiency. Finally, manual disassembly has potential health and safety risks. Criteria were established for the EoL EV batteries and various options were highlighted for handling these batteries [16]. The concept of a second life for EV batteries was introduced and several key technologies related to EV batteries were identified to accelerate the large-scale industrialization of second-life batteries. Artificial intelligence and Big Data technologies showed promise in second-life batteries.

3. Robotic Disassembly of EV Batteries

Researchers proposed innovative equipment and automation methods for the complex processes of battery disassembly. Ren Wei et al. [17] introduced a robotic disassembly and motion planning system for EV batteries. Experiments were conducted on a robot simulation platform with and without obstacles. The experimental results demonstrated that the system was capable of independently planning and completing a task in dynamic environment. The utilization of telerobotic technology to explore a semi-robotic disassembly approach was proposed by Jamie Hathaway et al. [18]. These researchers assessed the success rate and completion time of telerobotic technology in tasks such as disassembling bolts, grasping, and removing cover plates. The results showed a significant reduction in the overall disassembly time. However, the effect of the different levels of expertise of operators was not considered.

A disassembly planning system was constructed by defining disassembly primitives and introducing neural predictions. The intelligent disassembly of EV batteries was employed by deploying robots [19]. The utilization of industrial robots for battery dismantling was explored [8]. The disassembly process was analyzed, and the operation was divided into clamping and cutting. Robotic disassembly of EV batteries improved security and saved time compared to manual disassembly. An information-driven robotic disassembly architecture was proposed by Hendrik Poschmann et al. [20]. This system included an information marketplace, robot cognition processor, system perception unit, disassembly execution unit, and human–machine interface. The system could incorporate information from the product's entire lifecycle to ascertain the extent of disassembly.

4. Disassembly Sequence Planning and Knowledge Graph for the Disassembly of EV Batteries

Scholars created plans for disassembling returned parts that considered environmental factors and treatment methods. An automated optimization method was developed for planning disassembly sequences [21]. Components were classified in detail while separating them at the lowest level of disassembly to ensure the disposal of non-toxic, toxic, and safe components. The management of parts after EoL treatment was proposed to reduce the environmental impact of the whole process [22]. A disassembly sequence was created by using the stability graph cut-set approach and setting the minimum number of direction changes as the fitness function. By considering the direction changes through the fitness function, the stability graph cut-set method was utilized to generate the optimal disassembly sequence. A scoring system was designed to process the waste by decomposing the components containing biohazardous toxic materials to the lowest level [23]. An environmental risk reduction model was investigated which included various parameters to tackle medical electronic waste. Artificial intelligence, knowledge engineering, deep learning, and mathematical algorithms were employed to analyze the disassembly sequence planning of EoL products with varying levels of scrap or disassembly requirements.

Artificial intelligence and machine learning were used to optimize the battery disassembly process. The approaches of employing artificial intelligence and machine learning to assist the disassembly of EV batteries were investigated by Kai Meng et al. [24]. A machine learning and sensor-based automatic disassembly platform for EoL batteries was demonstrated [25]. This platform combined a computer vision system and a thermal imager to enable real-time control of the cutting action and to enhance safety and quality control throughout the disassembly process. Yang Hu et al. [26] proposed a knowledge recommendation system. This system employed a human–robot collaborative disassembly knowledge graph to assist human workers in disassembly operations and improve disassembly efficiency. The application of knowledge graphs was demonstrated. A review article discussed graph-based disassembly sequence planning [27]. Blocking Graph (with some variations), AND/OR Graph, Liaison Graph, Connector-based Graph methods, and other graph-based methods such as Contact State Graph were outlined.

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