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Intelligent disassembly of electric-vehicle batteries: a forward-looking overview

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ABSTRACT

Retired electric-vehicle lithium-ion battery (EV-LIB) packs pose severe environmental hazards. Efficient recovery of these spent batteries is a significant way to achieve closed-loop lifecycle management and a green circular economy. It is crucial for carbon neutralization, and for coping with the environmental and resource challenges associated with the energy transition. EV-LIB disassembly is recognized as a critical bottleneck for mass-scale recycling. Automated disassembly of EV-LIBs is extremely challenging due to the large variety and uncertainty of retired EV-LIBs. Recent advances in artificial intelligence (AI) / machine learning (ML) provide new ways for addressing these problems.

This study aims to provide a systematic review and forward-looking perspective on how AI/ML methodology can significantly boost EV-LIB intelligent disassembly for achieving sustainable recovery. This work examines the key advances and research opportunities of emerging intelligent technologies for EV-LIB disassembly, and recycling and reuse of industrial products in general. We show that AI could benefit the whole disassembly process, particularly addressing the uncertainty and safety issues. Currently, EV-LIB state prognostics, disassembly decision-making as well as target detection are indicated as promising areas to realize intelligence. The challenges still exist for extensive autonomy due to present AI's inherent limitations, mechanical and chemical complexities, and sustainable benefits concerns. This paper provides the practical map to direct how to implement EV-LIB intelligent disassembly as well as forward-looking perspectives for addressing these challenges.

1. Introduction

Electric vehicle (EV) battery recovery is critical to circular economy and sustainability. Today, the global EV fleet keeps growing and so are their Li-ion batteries (LIBs). According to the International Energy Agency survey, the worldwide stock of EVs at the end of 2020 was more than 10 million (IEA, 2021). The demand for EV-LIBs is rapidly increasing because of the consumers' growing commitment to sustainability and the push from governments and automakers. The annual EV-LIB demand to meet the sustainable development goal is projected to be more than 3 TWh in 2030. Since an EV-LIB with 20% capacity fade is considered end-of-life (EOL) battery, it is expected to see an exponential surge of retired EV-LIBs in the coming decade. These incoming retired EV-LIB waves pose severe environmental and societal risks to the environment. Spent EV-LIBs contain heavy metals in many cathode materials (e.g., $LiCoO_2$, $LiMn_2O_4$, and $LiNiO_2$) as well as toxic and corrosive electrolytes (e.g., $LiPF_6$) (Fan et al., 2020; An, 2019).

Accordingly, efficient and sustainable recovery of these spent batteries is required to realize the triple bottom line (TBL) of sustainability, which are economic, environmental and social sustainabilities (WCED, 1987). First, sustainable EV-LIB recovery creates business profits through scaled circularization of the EV-LIBs. As shown in Fig. 1 (a), there are three major options for the EOL battery, i.e., reuse, remanufacturing and recycling. Reuse, also known as repurposing or echelon reuse, is to apply those retired EV-LIBs with considerable remaining capacity into other systems such as energy storage systems (Martinez-Laserna et al., 2018; Hua et al., 2020; Reinhardt et al., 2019). Remanufacturing is to replace all the defective modules and/or cells to restore the EV-LIBs as good as new ones. A remanufactured LIB can be sold and utilized for its original purpose. Last but not least is material recycling. Material circulation is crucial to the valuable and critical resource (i.e., Co, Ni, and Li) conservation. The LIB recycling market is projected to be

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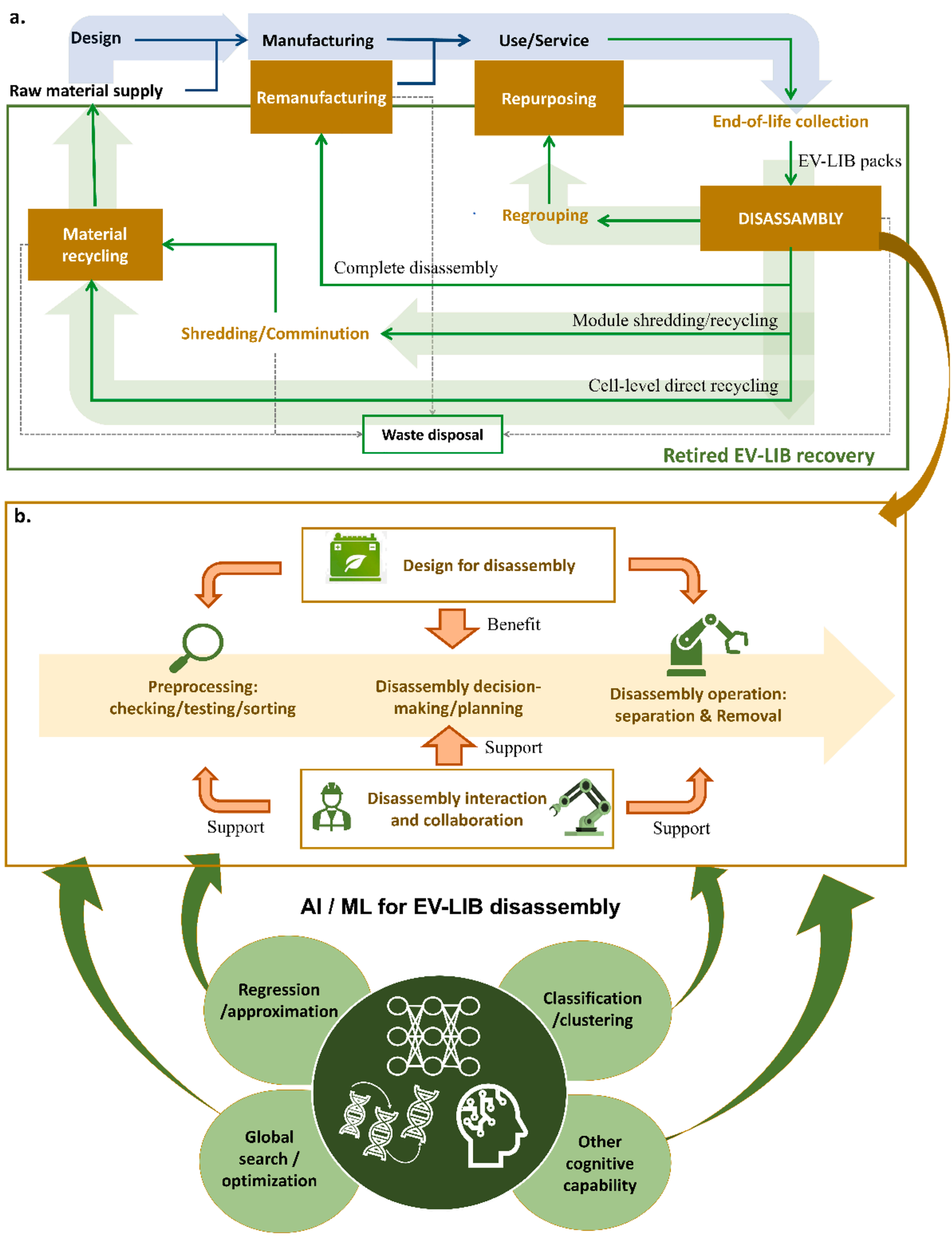


Fig. 1. Illustrations of EV-LIB recovery and disassembly: a. Closed-loop lifecycle management of EV-LIBs through sustainable recovery; b. A framework of intelligent disassembly.

USD 18.1 billion by 2030. All these sustainable recovery strategies can close the manufacturing and supply chain of EV-LIBs to bring scale economic benefits. Second, sustainable EV-LIB recovery eliminates environmental hazards. Reusing the materials and batteries save energy and resources, contributing to carbon neutralization by replacing mineral extraction and new material production. In addition, sustainable recovery business development can also create more jobs, reduce health risks, and improve labor well-being.

Aiming at such sustainable recovery of EV-LIBs, disassembly is recognized as one critical premise and a bottleneck process (Sassanelli et al., 2021). The current EV-LIB recycling process through comminution and metallurgy still carries unignorable environmental and safety risks. Shredding the whole LIB modules requires high energy and produces toxic gases and potential fires. Moreover, it mixes the anode and cathode materials, limiting the purity of material separation (Sommerville et al., 2020). Pyrometallurgy and hydrometallurgy are two major ways to extract and recycle valuable materials. The former relies on high-energy heating and smelting. Also, some materials cannot be recovered, such as electrolytes, graphite, and plastics (Chen et al., 2019). The latter requires chemical solvents. Thus, additional waste liquid treatment is needed. In addition, it cannot guarantee pure stream due to potential cross-contamination. A recent life-cycle analysis indicates that recovering EV-LIBs via these current recycling processes might not reduce greenhouse gas emissions compared to manufacturing new batteries (Ciez and Whitacre, 2019).

On the other hand, all sustainable recovery strategies require high-quality dismantling (Harper et al., 2019). For repurposing EV-LIBs, the retired EV-LIBs need to be partially or entirely disassembled and checked to eliminate the safety risks. The modules and cells require replacement, regrouping, and reconfiguring (Hua et al., 2020). For EV-LIB remanufacturing, complete disassembly and reassembly are needed (Sundin, 2004). Whatever an EV-LIB is reused or remanufactured, it cannot be refurbished too many times. Eventually, material recycling is inevitable. Direct recycling is an emerging sustainable recycling strategy. It recovers the materials from the cathode and anode of a cell by physical means without going back to elemental precursor forms. To this end, fine-granular sorting as well as cell-level disassembly are necessary. Therefore, the output quality of the EV-LIB disassembly will significantly affect all the downstream recovery processes (Sommerville et al., 2020). From the sustainability perspective, fine selective disassembly is a must-have process rather than an optional solution (Gerlitz et al., 2021). Such fine disassembly enables recovering the cathode/anode at the cell level and reclaiming all the other components in the pack and modules. Because of the tremendous amount of soon-to-be retired EV-LIBs, automated disassembly is a natural development to improve handling efficiency and quality. Unfortunately, high efficacy disassembly automation of EV-LIBs is extremely challenging due to the large variety and uncertainty within retired EV-LIBs, which will be further discussed in Section 3.

Artificial intelligence (AI) provides extraordinary ways for achieving intelligent disassembly. AI, particularly machine learning (ML), revives and rapidly flourishes as recent computing hardware and algorithm advances. Various nature-inspired intelligence techniques, e.g., neural networks and evolutionary computation, empower machines with enhanced learning capability to deal with nonlinear and complex circumstances. There are two reasons for AI to become a promising booster in sustainability. First, AI has demonstrated great potential in benefiting the product recovery business. Recovery activities can be optimized through intelligent robots/equipment, cloud services, and learning-based decision support systems to facilitate a sustainable closed-loop supply chain (Kerin and Pham, 2019; Meng et al., 2020; Ni et al., 2021). More importantly, almost all the disassembly automation techniques (e.g., object detection, robotic manipulation, system modeling and control, and disassembly planning) can find new effective ways through different learning strategies. It could be too ideal to say AI would lead to a rapid realization of intelligent disassembly, but it has already significantly increased the possibility of achieving it. Recent research also shows a promising landscape of smart recycling of EV-LIBs by mapping Industry 4.0 and smart manufacturing techniques into the recycling tasks (Blömeke et al., 2020). An information-driven robotic disassembly cell demo for EV-LIB modules is also developed in the EU-funded Recycling 4.0 project (Poschmann et al., 2021). Second, AI/ML has also played an emerging role in LIB research for scientific discovery and optimization (Aykol et al., 2020). These tools can help better understand the failure mode of LIBs (Blömeke et al., 2020), detect the internal short circuit (Naha et al., 2020), estimate the EOL health states and remaining useful life (Ng et al., 2020; Hsu et al., 2022), investigate the battery material characteristics (Deringer, 2020; Houchins and Viswanathan, 2020), and facilitate cloud-based prognostics and health management (PHM) of LIBs (Yang et al., 2020). All these advances potentially contribute to designing and implementing intelligent disassembly while incorporating domain-specific knowledge of EV-LIBs.

However, there is still a lack of systematic view on how to achieve EV-LIBs intelligent disassembly. There are several open Research Questions (RQ):

1) Why applying AI/ML is called for in EV-LIB sustainable disassembly and recovery?
2) How to select and apply various AI/ML methods to EV-LIBs intelligent disassembly?
3) What are the progress, opportunities, and challenges of EV-LIBs intelligent disassembly?

To address these questions, this study aims to provide an overall picture, practical insights, and forward-looking perspectives on AI/ML's application in revolutionizing or significantly improving the fundamental principles, processes, and implementation of EV-LIB disassembly. To our best knowledge, this is the first work that provides systematic answers to all these three research questions.

The remaining paper is organized as follows. Section 2 presents the research methodology and taxonomy. Then, based on the literature review, Section 3 analyzes the challenges for EV-LIB disassembly automation to answer RQ1. Section 4 conducts a systematic review on the intelligent methods for different EV-LIB disassembly processes (RQ2). Further, the contributions of existing studies as well as the opportunities, and challenges are discussed in Section 5 (RQ3). Finally, Section 6 concludes this paper.

2. Taxonomy and research methodology

This section first presents the taxonomy for classifying the technology subjects in this paper. Then the literature search method is presented.

2.1. Taxonomy

One major purpose of this review is to clarify how AI/ML can be integrated into EV-LIB disassembly activities. Therefore, a taxonomy is proposed from the perspective of EV-LIB disassembly process implementation. As shown in Fig. 1 (b), five key disassembly subjects are identified to classify different studies in this area:

1) Disassembly preprocessing. This is the first critical process for the EV-LIB returns to identify their specification, evaluate their EOL states, stabilize and sort them according to the quality states, and obtain essential information for disassembly and recovery processes. The results of these checking, testing, and sorting tasks determine the subsequent disassembly plan and recovery strategy.

2) Disassembly planning and decision-making. Based on the information obtained by preprocessing, disassembly decisions are made to determine, organize, and manage the disassembly activities.

The problems cover operational, tactical, and strategic decisions, including but not limited to disassembly process and task planning (Alfaro-Algaba and Ramirez, 2020), line balancing and scheduling, disassembly system layout design (Michalos et al., 2018), sustainability and risk assessment (Kazancoglu and Ozkan-Ozen, 2020), and the reverse logistic network design and control (Ai et al., 2019; Wang et al., 2020a).

3) Disassembly operation. This refers to the operational execution of the disassembly activities. Generally, it includes the detection, separation, and generic handling/grasping of the disassembly targets. More specifically, a) *disassembly target detection* recognizes the type and state of the object to be disassembled and localizes the object for further disassembly operations. Then, b) *separation operations* disconnect various types of connections in the EV-LIBs to get the modules, cells, and other components of interest. During and after the separation operations, c) *robotic manipulation* is required for autonomous grasping, handling, and removal of the components.

4) Disassembly interaction and collaboration. Human-machine interaction and collaboration are also indispensable to the operation and control of disassembly activities. Two work collaboration modes for EV-LIB disassembly are focused on in this paper. One is entirely remote control without sharing any physical workplace, a.k.a, teleoperation; the other one is human-robot collaboration to complete the disassembly together.

5) Design for disassembly. From the long-term and closed-loop lifecycle perspective, one vital mission is to incorporate disassembly considerations at the early design stage (Thompson et al., 2020), also referred to as design for disassembly (DFD) (Boorsma et al., 2020; Harivardhini et al., 2017). DFD potentially transfers the end-of-life knowledge back into the design and manufacturing of EV-LIBs. Consequently, the resulting eco-designs make all the disassembly processes easy, green, and efficient.

For each disassembly subject, the applications and potentials of primary AI/ML methods are examined in this work, as shown in Fig. 1 (b), including regression/approximation, classification/clustering, global search/optimization, and other cognitive and analysis methods.

2.2. Literature collection and screening

To collect the studies for this review, three groups of keywords are identified and utilized.

1) Keyword Group 1 (KG1): includes the elements regarding the EV-LIB product and its component, such as {electric vehicle battery, lithium-ion battery, LIB, power battery, battery pack, battery module, pouch cell}.

2) Keyword Group 2 (KG2): contains a set of keywords related to the disassembly and recovery subjects presented in Section 2.1 and Fig. 1 (b). Six subsets are utilized for guiding the search. One is for the general terms such as {disassembly, dismantling, recovery, remanufacturing, reuse, recycling}. The other five subsets comprise some detailed technology elements respectively for the five disassembly subjects. For instance, KG2-subset1 is for disassembly preprocess, including the keywords such as {checking, testing, sorting, screening, prognostics, RUL prediction}; KG2-subset3 includes the keywords disassembly operation such as {detection, grasping, manipulation, laser cutting}.

3) Keyword Group 3 (KG3): comprise the terms of AI/ML methods. KG3 also includes general and specific terms. The general terms utilize the keywords such as {AI, artificial intelligence, intelligent, machine learning, deep learning}. Other specific terms are generated from each AI/ML category shown in Fig. 1 (b), e.g., {neural network, DNN, Gaussian process, metaheuristic, GA, SVM, K-means, reinforce learning}.

The initial search is conducted in the scientific databases of Scopus, Science Direct, Web of Science, and Google Scholar. The period is set from 2010 to 2021. The search rule KG1 & KG2 is to examine the current states of EV-LIB disassembly and recovery. Then, the rule KG1 & KG2 & KG3 is to better identify the existing intelligent applications in EV-LIB disassembly and recovery. Further, KG2 & KG3 and KG1 & KG3 aim to explore the potentials of AI/ML for EV-LIB disassembly. All the materials obtained by the above rules are scrutinized. The studies published in recent 5 years regarding the integration of machine learning, especially deep learning, earned particular attention from the authors. Some representative papers commonly cited by the collected studies are also added. Finally, 123 papers are kept as the sample for this review.

3. Challenges for EV-LIB disassembly automation

This section first presents the current states of disassembly automation. Then the challenges and requirements of EV-LIB automated disassembly are analyzed and discussed to explain why intelligent methods are indispensable for facilitating this goal.

Disassembly automation can date back to around the 2000s (Karlsson and Järrhed, 2000). So far, various semi- and fully- automated disassembly system has been developed for waste electrical and electronic equipment (WEEE) dismantling and recycling (Basdere and Seliger, 2003; Kopacek and Kopacek, 2006). Most of the fine disassembly systems are bespoke disassembly systems dedicated to specific EOL products with known models. One well-known case is Apple's disassembly robot Daisy, which focuses on the iPhone disassembly (Apple, 2018). Noted that, to remove the glued battery from the iPhone body, the robot Daisy implements a blast process with -176 Fahrenheit degree freezing air. Similar sophistication should be required for EV-LIBs. Nowadays, EV-LIBs disassembly mainly relies on manual work and usually stops at the module level in the industry (Elwert et al., 2016). Fine cell-level disassembly is only conducted at the lab. There are some lab-level bespoke designs of EV-LIB disassembly machines (Li et al., 2019b; Wegener et al., 2015) and conceptual solutions to flexible EV-LIB disassembly systems (Fleischer et al., 2021). Nevertheless, according to our best knowledge, no industrial application of intelligent EV-LIB disassembly has been reported so far.

Current practice implies that there is still a long way to achieve autonomous disassembly for EV-LIBs. The reasons are mainly due to the following characteristics of retired EV-LIBs:

1) Safety risks. Spent EV-LIBs usually have heavy metals, toxic substances, volatile organics and even high voltage. Even the normal process of EV-LIB disassembly faces safety and health issues such as electric shock, short-circuit, thermal runaway or fires, and hazardous gas. Some special treatments, e.g., dissolving and destructive cutting, may increase the risk of higher toxic substance production or potential electrolyte leakage.

2) High design variety. At present, there is no standardized design for EV battery packs, modules, and non-cylindrical cells (Thompson et al., 2020). Although the importance of such standardization is widely recognized, it is not be easy to realize in the next decade. The increasing demand for mass customized design and production in the automobile industry will further complicate this issue as a tradeoff involving technical, commercial and societal interests. It is reasonable to expect that the retired EV-LIBs will differ in a broader range of architectures, configurations, sizes, shapes, capacities, and other physical and chemical properties in the coming decade.

3) Uncertain conditions. Like many waste electrical and electronic equipment (WEEE), the retired EV-LIBs will undoubtedly have significant differences and uncertainties in their performance and physical conditions, for instance, rusted, loosened, and even defective components, stained surface, and geometry change. An automated disassembly system must rely on intelligent perception to identify these circumstances and flexible handling capability to get rid of them.

4) Difficulties for robotic disassembly. An EV-LIB pack comprises multiple modules with numerous cells connected in various configurations with different mechanical, electrical, and chemical joining techniques. In addition, there are also different functional systems in a pack, e.g., battery management system (BMS) and thermal management system. Many of these components and connections are difficult for robotic manipulation, such as flexible cables and connectors/fasteners difficult to access. Moreover, various tough connections also prevent them from the automated, non-destructive, and easy separation of the components. One typical issue is the heavy use of adhesive bonding. Some thermal and welding joints are also challenging to process. Complex disassembly implementation in solvents or destructive cutting operations seems unavoidable for an automated process.

5) Lack of life-cycle data. The lack of data is more serious to those independent EV-LIB dismantling and recovery firms. Open data sharing for EV-LIBs is still not a reality due to business confidentiality and intellectual property considerations. Most collected EOL battery packs provide little information about their cell compositions. However, original EV and LIB manufacturers may also suffer from this issue as whole life cycle monitoring for each cell and component is still not practical. It is challenging to design an automated disassembly and recovery plan with insufficient information on these returns.

The safety risk is the first challenge for EV-LIB disassembly. Robotic disassembly can reduce the human health risk to some extent. However, due to the difficulties of robotic disassembly, human workers may have to work with robots and face potential harm from both the retired EV-LIBs and their robotic partners. To this end, on one side, it is desired to maximize the autonomy level of EV-LIB disassembly to minimize human involvement. On the other side, robust and reliable disassembly systems, as well as intelligent monitoring and management, are required to maintain safety in both automated disassembly and human-machine collaborations.

Second, varieties and uncertainties of spent EV-LIBs significantly increase the difficulty and cost of mass disassembly and recovery. These two challenges make fine selective disassembly not the exact reverse of assembly but more complicated, calling for a disassembly system with high flexibility. Usually, it is not feasible to determine a unified disassembly plan and route for all the end-of-life product returns. Disassembly depth also varies depending on the health state and recovery goals of an individual EV-LIB. Therefore, even a bespoke automated disassembly system may fail if it cannot deal with various uncertain circumstances (Chen et al., 2021). The autonomous disassembly system is expected to have high flexibility, adaptiveness, and perceptual capability in all the disassembly processes to recognize and handle various scenarios. Further, difficulties for robotic disassembly call for highly efficient separation processes and human-robot collaborations.

In addition, the lack of life-cycle data impedes efficient and effective disassembly decision-making. EV-LIB disassembly involves multi-level decision-making. From pack to the module and then down to the cell, sequential disassembly decisions need to be made to determine the optimal disassembly depth and how to separate and remove the cover, electrical/mechanical/chemical connections, electronic components, modules, cells, and even cathode, anode, separator and electrolyte in the cell (Wegener et al., 2014; Kampker et al., 2020). While skilled experts are needed for manual disassembly, well-built detection and knowledge systems on the EV-LIB specification and characteristics are necessary for automated disassembly.

In summary, all five challenges determine that an automated EV-LIBs disassembly system would not be successful without incorporating a certain level of machine intelligence. To some extent, automation and intelligence capacity should be built simultaneously for EV-LIB disassembly. A successful disassembly automation system is an organic system requiring multi-dimensional cognitive capability. A typical disassembly system consists of various sub-systems, including but not limited to robots/ manipulators, disassembly tools, fixture systems, sensing systems, internal logistical systems, control and management system, and human worker stations (Vongbunyong and Chen, 2015). Managing such a system requires multi-dimensional perception and intelligent decisions to achieve adaptive and flexible automation (Vongbunyong and Chen, 2015; Poschmann et al., 2020). It should be noted that even if standardized and eco-designed EV-LIBs are available, most of these intelligent requirements remain significant to guarantee sustainable disassembly and recovery. Improved design of EV-LIBs can reduce the difficulties of component separation and manipulation; however, battery condition uncertainty will still exist, which cannot be eliminated. A bespoke robotic system for possible standardized EV-LIBs still requires perception and flexibility to manage uncertainty. Fortunately, AI/ML enables new solutions to overcome some of these challenges.

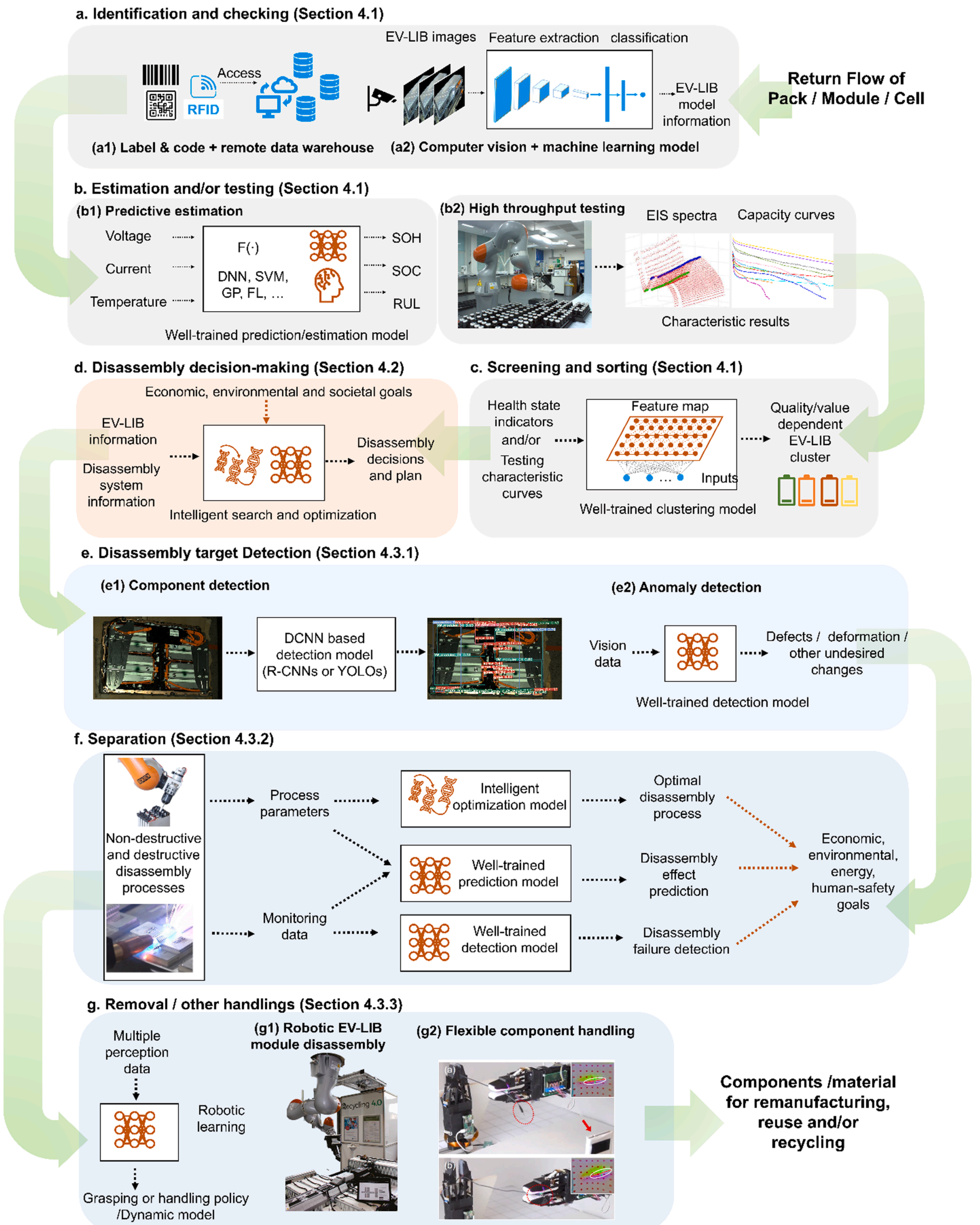
4. Intelligent methods for EV-LIB disassembly processes

This section reviews the applications and potentials of AI/ML methods. An overall view of basic operations in EV-LIB intelligent disassembly is illustrated in Fig. 2.

4.1. Intelligent preprocessing of EV-LIB

Checking, testing and sorting are critical preprocessing tasks in identifying the specification of the spent EV-LIBs and evaluating their condition and quality (Sommerville et al., 2020; Ng et al., 2020). It is evident that the disassembly and recovery value of an EV-LIB highly depends on its EOL health state, usually indicated by the state of health (SOH), state of charge (SOC) and remaining useful life (RUL). Under- or over-estimation will lead to failed disassembly and negative sustainable benefits (Zhou and Piramuthu, 2013). In addition to the observation check, various non-destructive testing methods have been suggested (Xiong et al., 2020; Pastor-Fernández et al., 2019), such as electrochemical impedance spectroscopy (EIS), ultrasonic testing, and X-ray computed tomography. Nevertheless, there are still gaps for intelligent testing and sorting to achieve high-throughput testing and sorting. Current checking and testing techniques cannot provide accurate and thorough assessments for each model and individual cell without dismantling the pack. Even after the disassembly operations, there is no mature technology and equipment capable of fast detecting and screening battery modules/cells. Moreover, since EV-LIBs have a hierarchical architecture with tens of modules and numerous cells, checking and testing are not one-shot work but recurrent requirements during the disassembly operations from pack to cell level (Kampker et al., 2020). These testing processes also incur costs (Chen et al., 2019; Kampker et al., 2020.

To close these gaps, intelligent techniques provide some exciting solutions to rapidly check, test, and sort. One widely-used method for industrial checking and recognition is intelligent labeling technology for EV-LIBs, e.g., radical frequency identification (RFID) (Wessel, et al., 2020; Garrido-Hidalgo et al., 2020). This technique can provide contactless and unique identification while simplifying the acquisition, tracking, and tracing of EV-LIB model information. But it also requires well-built Internet of Things (IoT) system, widely recognized standards for information interoperation, and open data sharing (Fig. 2 (a1)). Some standards for LIB labels have been suggested by the Society of Automotive Engineers (SAE). Another intelligent solution is combining computer vision (CV) with convolutional neural network (CNN), which has been suggested as one promising fast waste classifier for recycling (Chu et al., 2018; Zhang et al., 2021) (Fig. 2 (a2)). CNN-based CV can recognize and classify the items simultaneously. A recent study on CNN-based recognition and classification reported the accuracy from



(caption on next page)

Fig. 2. Basic operations in EV-LIB intelligent disassembly. (a) Returned EV-LIBs or their modules/cells are recognized and checked to obtain necessary information for disassembly and recovery operations. EV-LIB pictures are adapted from (Rallo et al.,2020), (b) The health states and characteristics of these EV-LIB packs/-modules/cells need to be evaluated and tested before disassembly in an intelligent and high throughput way. The robotic experiment scenario is reprinted from (Burger et al., 2020), The characteristics results are reprinted from (Zhang et al., 2020a). (c) The returns are classified or clustered according to their quality and characteristics to match appropriate disassembly and recovery plans. (d) Multi-level disassembly decisions and plans are made by intelligent methods to achieve economic, environmental and societal sustainability, (e) Disassembly targets, including functional components and fasteners, are detected based on sensory data and deep learning. EV-LIB pack detection: (Choux et al., 2021),. (f) Both destructive and non-destructive separation operations can be optimized by intelligent methods through process parameter optimization, disassembly effect prediction and disassembly failure detection. Robotic separation: adapted from (Wegener et al., 2015); Laser cutting: reprinted from (Kampker et al., 2020). (g) Intelligent techniques are also crucial for other handling operations in disassembly, such as flexible component handling (She et al., 2019), as well as disassembly system integration and control. The figure in (g1) is adapted from (Poschmann, Brüggemann and Goldmann, 2021).

90% to 97% for checking three classes of WEEE products (180 training images and 60 testing images) (Nowakowski and Pamuła, 2020). Compared to the intelligent labels, it is more adaptive and easier to implement, but the accuracy and reliability are lower than the unique identification techniques.

As for the battery health states estimation, intelligent prognostics provide new solutions based on condition monitoring data. Smart BMS are constantly improving to enhance the online data acquisition of battery's conditions such as voltage, current and temperature (Xiong et al., 2018). Various prognostics models and approaches have been proposed, including physical models (e.g., equivalent circuit model, electrochemical model, thermal model), data-driven models, and hybrid models that combine the advantages of physical and data-driven models. Among these studies, AI shows strong power in modeling such complex and time-varying battery systems to predict the states of LIBs without the need for expert knowledge (Fig.2(b1)). Almost all kinds of AI/ML methods have been tried, such as neural network(NN) (Wu et al., 2018; Zhang et al., 2018), Gaussian process (Richardson et al., 2017; Zhang et al., 2020a) support vector machine (SVM) (Nuhic et al., 2013), and fuzzy logic (Razavi-Far et al., 2016; Zahid et al., 2018), just to name a

Table 1
Typical intelligent methods for disassembly preprocessing

Tasks	Methods	Advantages	Disadvantages	Ref.
Identification and checking	Intelligent labeling (RFID)	•Non-contact and unique identification •Highly efficient reading and writing •Easy acquisition, tracking and tracing of EV-LIB model information •More reliable compared to human checking and bar-code	•Additional investments for RFID devices and system •Data sharing, privacy and safety •Require standards for EV-LIB labeling and information interoperation	(Wessel, et al. 2020) (Garrido-Hidalgo et al. 2020)
	CNN based computer vision	•Fast and adaptive •Only image input needed •Capable of simultaneous recognition and classification	•Require sufficient data (image) sets for training and testing •No standard design of the neural network configuration •Performance dependent on the imaging condition, training quality and EOL battery uncertainty	(Chu et al., 2018) (Nowakowski and Pamuła, 2020) (Zhang et al., 2021)
Health state prognostics	ANN	•Model-free design •Strong learning capability for nonlinear and black-box scenarios •Capable of handling large scale samples	•Require sufficient training and testing •No standard design of the neural network configuration •Not easy to estimate the confidence and uncertainty	(Wu et al., 2018) (Zhang et al., 2018)
	Gaussian process	•Non-linear processing ability •Probability based uncertainty estimation	•High computation burden for maximum likelihood estimation and optimization Intractable for large-scale data sets •Prior assumption of Gaussian distribution	(Richardson et al., 2017) (Zhang et al., 2020a)
	SVM	•Capable of handling high-dimension and nonlinear features •Small sample learning	•High computation burden for large-scale datasets •No standard method for the selection of Kernel functions	(Nuhic et al., 2013)
	Neural fuzzy inference	•Capable of handling fuzzy and non-structural information •Inference capability by incorporating expert knowledge and rules	•Require sufficient training and testing •No standard design of the neural network configuration •Subjective design of fuzzy rules	(Razavi-Far et al., 2016) (Zahid et al., 2018)
Screening	Radial basis function neural network	•Model-free learning •Strong prediction capability of battery characteristics	•Require labeled data •Require sufficient training and testing	(Zhou et al., 2020a)
	Improved Bi-K-means algorithm	•Unsupervised learning and hierarchical clustering •Lower sensitivity to noise compared to traditional K-means Fast and simple	•Predetermined cluster number K •Not suitable for non-convex cluster	(Zhou et al., 2020b)
	Self-organizing map neural network	•Unsupervised competitive learning and clustering •Capable of handling high dimension features •Visualization capability	•No standard design for the grid •No guarantee of convergence High training and computation burden for large scale datasets	(Garg et al., 2020)
	SVM	•Supervised learning and classification •Capable of handling high-dimension and nonlinear features •Small sample learning	•Require labeled data •High computation burden for large-scale datasets •No standard method for the selection of Kernel functions	(Zhou et al., 2020c) (Lai et al., 2021)

few. For more details, refer the readers to some latest reviews (Hu et al., 2019; Hu et al., 2020; Lipu et al., 2018; Meng and Li, 2019; Ng et al., 2020). The pros and cons of these methods are summarized in Table 1.

These intelligent prognostics approaches provide domain-knowledge-free ways to explore the implicit degradation mechanism of the EV-LIBs. A reliable prediction of the quality states of EV-LIBs can significantly reduce the preprocessing time and cost. Nevertheless, it should be noted that prognostics may currently perform as decision assistance rather than replacing all the testing procedures. In practice, multi-scale, accurate, and robust estimation is still challenging. Pack- and module-level assessments are complicated due to the heterogeneous states of cells. Even for cell-level, an accurate estimation that covers all the individual cells is impossible for now. Current commercial BMS has a collection precision of cell voltage around 5 mV(Lu et al., 2013) and cannot provide accurate SOH and RUL predictions(Waag et al., 2014). Also, in a recent survey, the averaged prediction error of the recent studies on AI-based battery state estimation is 4.0% for SOC, 5.0% for SOH, and 4.1% for RUL (15 studies on SOC, prediction error from 0.1%-13%; 5 studies on SOH, prediction error from 1.6%-7%; 8 studies on RUL, prediction error from 0.2%-9.1%) (Ng et al., 2020). It can be seen that the prediction errors are highly variable for different scenarios and technology scales. Consequently, one should be cautious to conclude that they are ready for mass applications in industrial settings considering their unproved robustness and potential loss for the mis-estimations. High-throughput testing of EV-LIBs through robots is also attractive and crucial (Ng et al., 2020). Nowadays, robot-assisted testing is practical through combining autonomous mobile robots and intelligent analysis capability (Burger et al., 2020) (Fig. 2(b2)).

Intelligent methods can also contribute to battery screening. Usually, estimated or testing capacity, resistance, and voltage features are utilized to cluster and sort retired EV-LIBs, modules, and cells (Fig. 2(c)). Different ML models are trained and applied to extract these characteristic features and then sort or screen the EV-LIBs according to their qualities. One approach is supervised learning-based classification, e.g., radial basis function neural network (Zhou et al., 2020a). and supporting vector machine (Zhou et al., 2020c; Lai et al., 2021). This approach requires sufficient labeled data for training and testing. To avoid tedious and non-intuitive work for EV-LIB classification labeling, the other one is unsupervised learning-based clustering, such as self-organizing map neural network (Garg et al., 2020), and improved bisecting K-means algorithm (Zhou et al., 2020b). The intelligent and fast screening process can provide quality-dependent information for the subsequent disassembly decision-making, such as determining different disassembly depths for different EV-LIB categories.

4.2. *Intelligent disassembly planning and decision-making*

EV-LIBs disassembly management involves various decision-making and planning problems, which is more complex than the assembly process. For instance, in a human-robot collaborative disassembly system, to maximize the economic and environmental benefits, one needs to determine (i) what are the best process route and disassembly depth to disassemble an EV-LIBs, (ii) which tasks should be assigned to the robots while the others to the humans, (iii) which tasks associated their required disassembly resources should be assigned to a specific robotic, human, or collaborative workstation. Due to the disassembly uncertainty, reasoning and cognitive capability are needed for dynamic and adaptive planning in a digital disassembly factory (Poschmann et al., 2021). The disassembly plan and task assignment should be adjusted smartly as the EV-LIB return flow and disassembly orders change (Laili et al., 2019).

Intelligent methods can support such disassembly decisions (Fig. 3). The disassembly planning and scheduling problems are usually formulated as mathematical programming and global optimization problems. Various graph-theory methods (e.g., directed graph and AND/OR graph) are also applied to model those physical and sequence relationships to convert the problem into a global graph search. Because of the complexity of the model and its decision space, the computation time will dramatically increase as the input space scales. Therefore, it is common to encounter computation challenges (e.g., NP-hard problem) when solving a large-scale programming problem. Despite today's powerful computing capability, brute-force enumeration is not an economically and technically sound solution. Therefore, plenty of researchers proposed various metaheuristic approaches based on different evolution or iterative computation algorithms to optimize the disassembly sequence and robotic line balancing while considering multiple sustainable goals (Liu et al., 2020; Feng et al., 2018; Fang et al., 2019; Wang et al., 2019). Metaheuristic algorithms such as the genetic algorithms (GA) and swarm optimization algorithms, have been demonstrated to be effective for these disassembly planning and scheduling problems. Decision variables are coded into a nature-inspired population while various economic, environmental, and societal performance goals guide the evolution of the population with judiciously designed metaheuristic or heuristic rules. The optimal solution is identified by an iterative search. Such search approaches, which also occur in nature, can handle the non-convex and nonlinear and even black-box global optimization problems. However, usually, only approximately global optima can be obtained.

In real-world disassembly, the disassembly system usually needs to interact with the environment, deal with uncertain scenarios and make sequential disassembly decisions. Some studies suggested reinforcement learning (RL) methods to solve the stochastic and sequential disassembly decision-making problems (Tuncel et al. 2014; Xia et al. 2014; Mei and Fang, 2021). Another promising option is combining smart hardware technologies (e.g. augmented reality (AR)) with metaheuristic optimization or RL to facilitate interactive disassembly decision-making (Chang, Nee and Ong, 2020) .

Both metaheuristic algorithms and RL are iterative. The iteration and convergence speed could be very slow, limiting their application for large-scale problems and online optimization with high real-time requirements. With the hope of taking full advantage of the neural network's end-to-end fast output capability, recently, DNN methods have been introduced into solving such programming problems, particularly combinatorial optimization problems (COPs). Typical examples are using sequence-to-sequence mapping networks such as pointer network (Vinyals et al., 2015; Bello et al., 2016), Transformer attention (Kool et al., 2019), and Graph pointer network (Ma et al., 2020). These methods have been successfully applied to some classical planning problems, e.g. traveling salesman problem. However, their optimization capability, robustness, and convergence require further validations in practice compared to metaheuristic algorithms and exact methods. A detailed comparison of these methods is summarized in Table 2.

The emerging DNN methods provide some intriguing ways for fast, high-level, model-free, and intelligent disassembly decisions, reducing the limits caused by different assumptions and intermediate variables. One example is to explore a mapping directly from the sensory and testing data into the disassembly decision, i.e., disassembly depth and plan. Currently, the testing result is not directly equivalent to a disassembly and recovery decision. Even given the quality grade information, the relationship between SOH/SOC/RUL and recovery value remains complex and unclear.

Another attractive conceptual solution is cloud-based EV-LIB disassembly. Based on the public, community, and private clouds, all the stakeholders in the EV-LIB disassembly chain, from EV and LIB designer to the EV-LIB recovery firms, are connected to share the data and knowledge, optimize the utilization of disassembly resources and capacity, and improve the collection and disassembly service. Various software services can also be shared and enhanced by the cloud, such as intelligent life cycle assessment and closed-loop EV-LIB supply chain management. The potential incorporation of blockchain techniques into the cloud service could dispel privacy and confidential concerns for information tracking and sharing, leading to more active disassembly

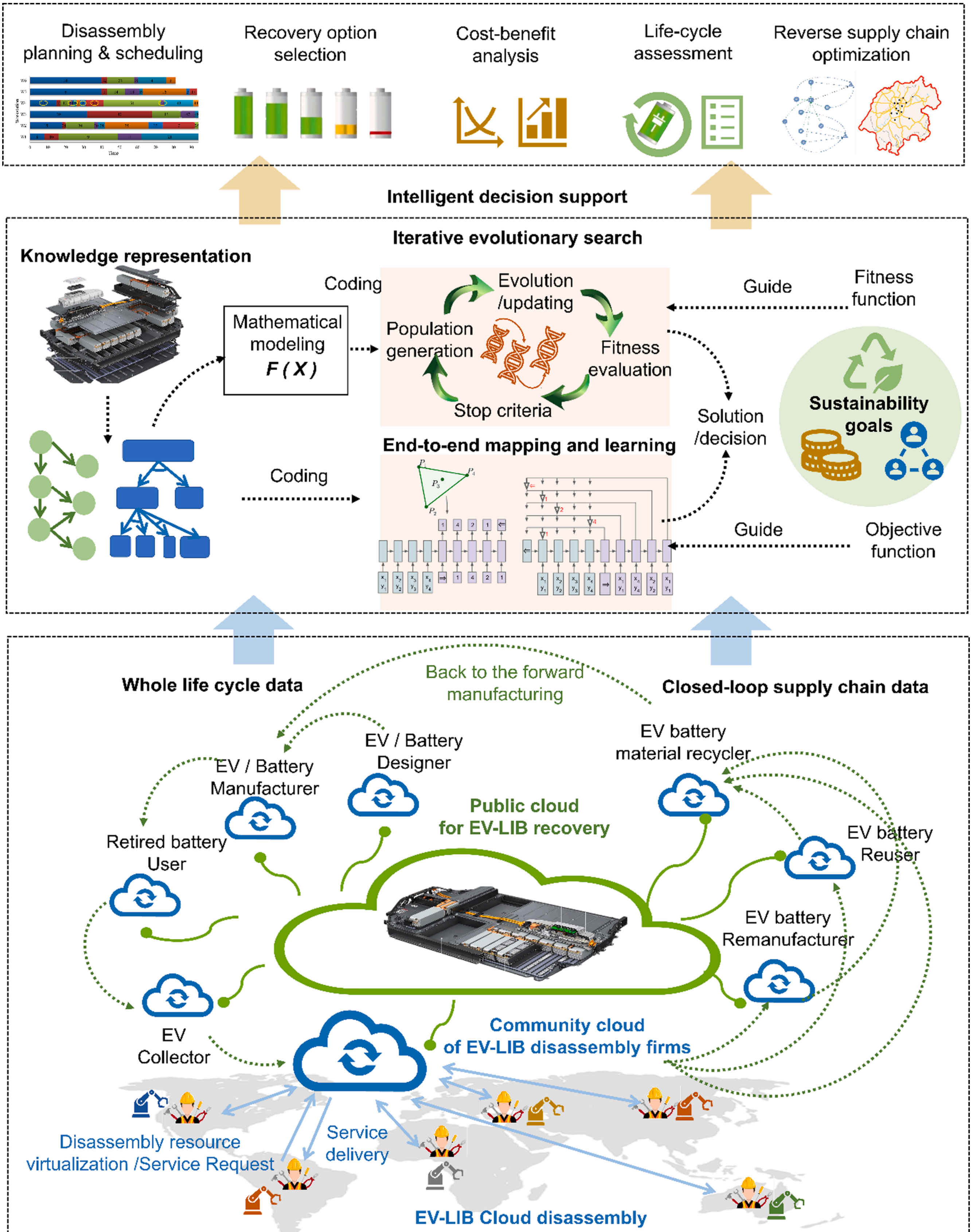


Fig. 3. Intelligent management of EV-LIB disassembly. EV-LIBs: reprinted from Audi e-tron Sportback 2021(Audi, 2021a)(Audi, 2021b); Model-free mapping and learning: reprinted from (Vinyals et al., 2015); Disassembly planning and scheduling: reprinted from Wang et al. (Wang et al., 2019); Reverse supply chain optimization: reprinted from Wang et al. (Wang, Wang and Yang, 2020b)

Table 2
Typical intelligent methods for disassembly planning and decision-making

Methods		Advantages	Disadvantages		Ref.
Metaheuristics optimization algorithms	GA, MOGA and its variants	•Random and global search •Problem model independent •Parallelism •Capable of handling non-convex and black-box scenarios	•Require coding/decoding mechanism design •No guarantee on global optima •Prone to local optima •Initialization dependent	•No memory •Poor local search ability	(Ren et al., 2018) (Fang et al., 2019) (Feng et al., 2018)
	Swarm optimization (ACO, ABC, etc.)		•Require expertise on algorithm design and parameter tuning •Slow iteration for large scale problems	No mature convergence analysis compared to GA	(Laili et al., 2019) (Tseng et al. 2019) (Liu et al., 2020)
Machine learning	RL (Q-learning, Deep RL)	•Capable of handling stochastic and uncertain disassembly environment •Suitable for sequential decision problems •Self-learning capability	•Require expertise on reward function design and parameter tuning •Slow iteration for large scale problems •No guarantee on stability and global optima		(Tuncel et al. 2014) (Xia et al. 2014) (Mei and Fang, 2021)
	Attention Mechanism/GNN	•No need for domain knowledge •End to end mapping •Fast and easy to implement •Strong generalization capability	•Require sufficient training •Not easy for constraint handling •No guarantee on global optima •No proven application in disassembly decision problems		(Vinyals et al., 2015) (Bello et al., 2016) (Kool et al., 2019) (Ma et al., 2020)
Hybrid intelligent methods	AR + MOGA	•Online real-time planning •Interactive disassembly decision making	•Additional investment for AR system •Slow iteration for large scale problems •No validation for complex disassembly tasks		(Chen, Zhang and Zhou, 2020a)
	DQL+GA+VR	•Adaptive planning for unpredictable disassembly targets •avoid dependence on the immediate reward	•Slow iteration for large scale problems •No guarantee on stability and global optima •No validation for complex disassembly tasks		(Mao et al., 2021)

Table 3
Typical intelligent methods for disassembly operations

Tasks	Methods	Advantages	Disadvantages	Ref.
Computer vision based disassembly target detection	Region-proposal based two-stage detection	•Bottom-to-up selective search •Separate steps for region proposal and region classification •High detection accuracy •Capable of handling multi-scale and small object detection	•Slow learning speed compared to single stage models •Complex architectures	R-CNN for PCB component detection: (Kuo et al., 2019) Mask R-CNN + FPN + Adaptive Pooling + Edge Detection (Jahanian et al., 2019) Faster RCNN +Inception_ResNet v2 for EV battery screw detection : (Poschmann et al., 2021)
	Region free one-stage detection	•Global regression Simple pipeline •High learning speed for real-time detection	Low localization precision for small objects compared to region proposal-based models	YOLO v3 for EV pack detection: (Choux et al., 2021)
Cutting process optimization	Multi-objective metaheuristic optimization	Global search in the process combinatorial parameter space	•Local optima •Slow convergence for large scale optimization	(Rao et al., 2017)
	Clustering/ classification	Capable of identifying the relationships between the process inputs and outputs	•Lack of sufficient experimental data	(Tercan et al., 2017)
	Neural network	Prediction ability of the process effect	•Require sufficient training •Lack of sufficient experimental data	(Anicic et al., 2017)
Robotic grasping /handling	Sim2real learning with domain randomization for universal picking	No need for tedious empirical data collections	•High computation burden in synthetic dataset generation •Dependent on the training dataset •Simulation-to-reality gap	(Mahler et al., 2019)
	Self-supervised learning	•Automatically collect unlabeled real-world data for learning •No need for expensive manual labeling	•Require expertise on pretext task design	(Deng et al. 2019) (Yan et al. 2020) (Fang et al., 2020)
	Learning from imitation/ demonstration	•No need to manually specify imprecise models •No need for prior reward function design	•Require high quality and sufficient demonstrations •Limited generalization capability	(Lin and Sun, 2015) (Xie et al. 2020)
	Combined self-supervised and imitation learning for deformable objective manipulation	Combining the learned goal-directed inverse dynamics model with high-level human direction	Limited generalization capability for new objects and complex tasks	(Nair et al., 2017)

cooperation between OEMs and third-party disassembly partners.

4.3. Intelligent disassembly operation

This section reviews the AI/ML-based methodologies that have already contributed or will potentially contribute to the disassembly operations. The typical intelligent methods for these disassembly tasks are summarized in Table 3 and discussed one by one as follows.

4.3.1. Disassembly target detection

The states of the EV-LIBs comprise static features and dynamic changes. The former refers to the geometric and physical information necessary for implementing a disassembly operation, such as pose, position, shape, and rigidity, to name a few (Wang et al., 2020a). To reduce the disassembly uncertainties, the detection includes recognizing any possible defects and abnormal states of the disassembly target to cancel or change the disassembly implementation. The latter requires identifying the state variation during and after the disassembly operation to guarantee successful and safe disassembly.

A typical intelligent detection process learns the mapping between the sensing data and the state of the disassembly object. Various sensors have been adopted, such as passive 2D/3D industrial cameras, force and torque sensors, tactile sensors, and active illuminators. Force/torque sensors are necessary for effective contact detecting, disassembly effects checking, and motion control purposes. Computer vision is the most popular one due to its high accuracy, flexibility, generalizability, and easy implementation. RGB and depth images are the most common inputs to extract the features, aka the segmentation process. In addition to traditional image processing methods (e.g., thresholding and template matching), intelligent algorithms are one popular stream for dealing with complex and uncertain detection objects. Feature classification is usually conducted by AI methods such as fuzzy measures, ANN, SVM, and decision trees.

Recently, deep learning combined with machine vision has shown powerful capabilities in performing the detection (Zhao et al., 2019). One extraordinary advantage of deep learning is that it is possible to simultaneously complete the feature extraction, classification, localization, and labeling through multi-task learning. There are two generic frameworks to conduct the learning for detection in the scene. One is to first generate and select candidate regions in one image and then perform convolution and other processing operations for these regions. This DNN based method is referred to as the region proposal based method, including region CNN (R-CNN) (Fig. 4 (a)) and its variants (e.g., Fast R-CNN, Faster R-CNN, and Mask R-CNN) (He et al., 2020). The other one is to treat the image as a whole through global regression in real-time, e.g., You Only Look Once (YOLO) algorithm (Fig. 4 (b)) and its variants.

The R-CNN series of models provide higher detection accuracy than the YOLO models. Therefore, they are widely used in handling multi-scale and small object detection. Some preliminary studies

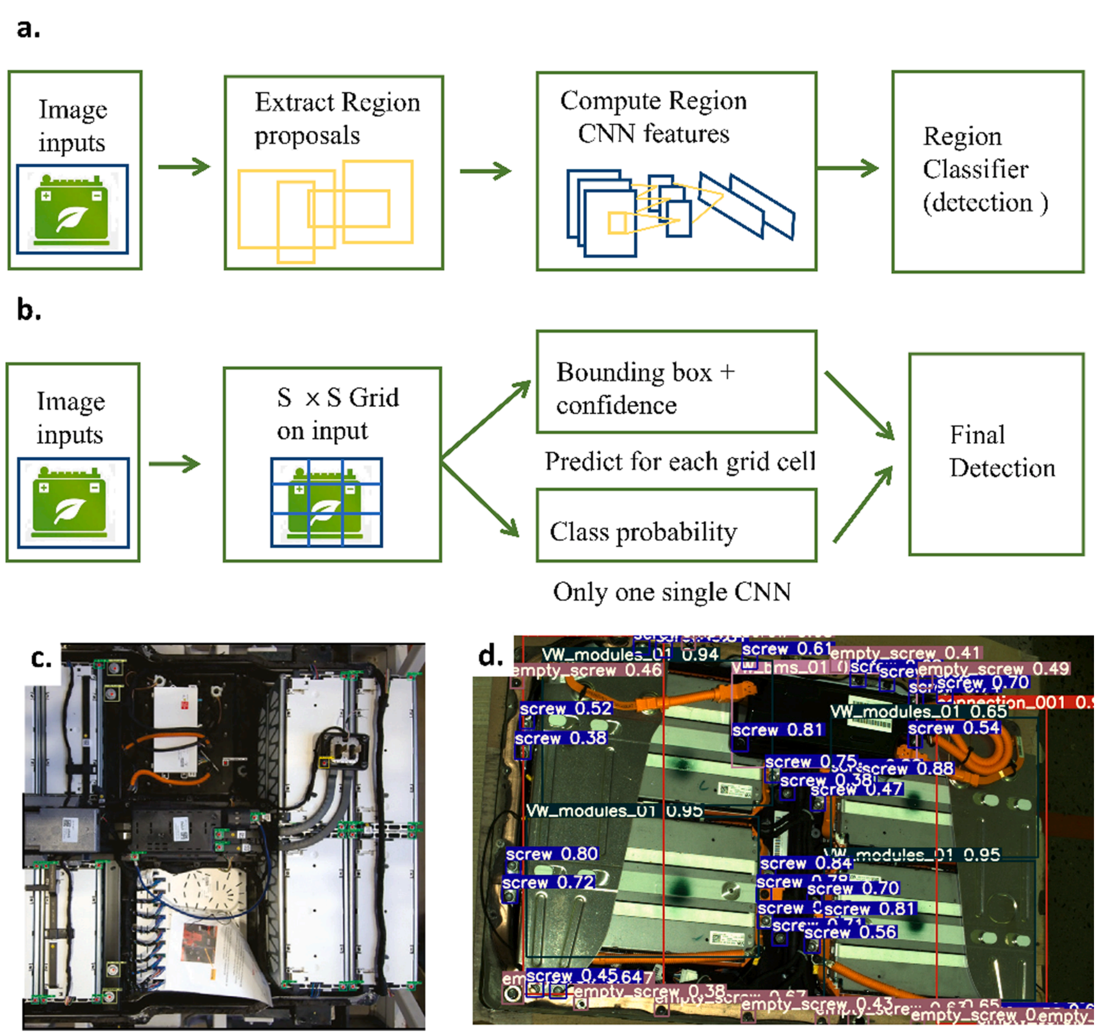


Fig. 4. CNN-based disassembly target detection. a. The basic idea of R-CNN model (Girshick et al., 2014); b. The basic idea of YOLO model (Redmon et al., 2016); c. Screw detection by Faster-RCNN, reprinted from (Poschmann et al., 2021)); d. EV-LIB pack component detection by YOLO v3, reprinted from (Choux et al., 2021).

demonstrate their potentials for fast detection of tiny components in disassembly scenarios, including EV-LIB disassembly. One typical application is to detect the small components on a printed circuit board (PCB) through well-trained DNNs. To better distinguish those high-density components with similar appearance, R-CNN can be integrated with a similarity learning network (Kuo et al., 2019). Object detection in the recycling context also requires advanced methods such as precise edge detection. Multi-task learning has also been leveraged for E-waste component recycling to achieve object detection, localization, instance semantic segmentation, and boundary detection, where R-CNNs are combined with edge detection (Jahanian et al., 2019). Recently, universal screw detecting CNNs was developed based on (Yildiz and Wörgötter. 20192020). Further, Poschmann et al., (2021) successfully applied Faster-RCNN detection models into the perception unit for a demonstrator EV-LIB disassembly cell. This work demonstrates a detection accuracy of 73.71% and average localization precision of 0.86 mm for the TX30_M6 $\times$ 12 screws (training on 500 labeled images) (Fig. 4 (c)). Compared to the R-CNN family, the merit of YOLOs is their high speed for real-time detection. A recent work utilized YOLO v3 for the detection of different components in an EV-LIB pack, such as screws, BMS, connecting plates, as shown in Fig. 4(d) (Choux et al., 2021).

Some challenges in industrial disassembly scenarios may pose challenges for object detection, such as complex background, insufficient spent LIB RGB-D data, and irregular shapes of fasteners or defective parts. Nevertheless, huge progress is still being made to constantly improve the precision, robustness, and real-time performance of intelligent detection.

In addition, intelligent defect detection has been widely proven in general industrial applications. Most disassembly target appearance uncertainties described in Section 3 can potentially be recognized through surface defect detection using machine vision and deep learning (Chen and Jahanshahi, 2018; Lian et al., 2020; Tabernik et al., 2020; Xu, Lv, Deng and Li, 2020)). It is also promising to monitor the disassembly failure and final disassembly effects. To this end, beyond recognition, further inference and analysis are required to support the disassembly decisions.

4.3.2. *Separation process optimization*

Separation of EV-LIB components requires disconnecting various types of connections. The primary types include electrical connections, mechanical fasteners (e.g., nut and bolt, spring clasp, screw, snap-fits, and clinching), welding and soldering joints through various welding processes, and adhesive joints for electrical insulation, sealing, and heat conductors (Das et al., 2018). Non-destructive disassembly methods, e.g., unscrewing and selective de-soldering, are highly recommended for reusing and remanufacturing some components. To flexibly handle all the above-mentioned joints, it is necessary to enable the disassembly system with varying tools and fast multi-tool change capability. Destructive and backup operations, e.g., cutting, milling, or drilling, are also inevitable for current LIB designs due to the uncertainties in product condition (e.g., joint failure) and some hardly disconnected joints (e.g., adhesive joints).

The separation process seeks more energy-efficient, waste-reducing, damage-minimizing, and human-safe ways. Such separation should be flexible and adjustable to choose the optimal separation technique, tool and process parameters for each pack/module/cell according to its EOL state. Intelligent technologies can optimize the separation processes and monitor the operation effects (Fig.2(f)). For instance, in robotic unscrewing and unfastening, monitoring the toque and position can better engage the tool to the screw (Li et al., 2020b) or avoid screwdriver slippage (Mironov et al., 2018). Laser cutting can be used for high-quality cuts of metal, alloy, and even adhesive joints. The cutting parameters directly affect the disassembly efficiency, energy consumption and associated carbon emissions (Kumar Pandey and Kumar Dubey, 2012). AI/ML is leveraged to identify the optimal process parameters, e.g., gas pressure, pulse property, cutting speed, and kerf taper, under predetermined performance objectives (Kim et al., 2018; Tercan et al., 2017; Rao et al., 2017; Singh et al., 2021). To evaluate the cutting effects for minimizing destroys, ML can also predict the heat-affected zone of the laser cutting process (Anicic et al., 2017). These cutting process optimizations are helpful to minimize the technical, environmental, and safety impacts of destructive disassembly operations on the retired EV-LIBs.

4.3.3. *Dexterous robotic manipulation for disassembly*

Dexterous robotic manipulation is essential for intelligent disassembly. Some bespoke disassembly machines can remove and collect a batch of components without dexterous and selective handling, such as vibration and sweeping. These operations usually require hard coding, auxiliary tools and fixtures, as well as fixed equipment design. These "hard" operations are far from reaching intelligent disassembly goals due to a lack of flexibility and adaptiveness to deal with disassembly uncertainties. The uncertainty stems from either randomness of EV-LIB state, disassembly system and environment, or imperfect control models. However, dexterous manipulation is also a world-class challenging task for robotics research. Even a simple manipulation for humans, such as pick-and-place, is not always easy for robots. In a pick-and-place task, the disassembly robot needs to detect and localize the component, plan the path of its motion, find a stable grasp position and pose with given gripper design, monitor the motion to avoid slippage, and make sure the component can be stably put in a correct place (Mason, 2018). Some soft and irregular shape components in an EV-LIB, such as cables and non-standard fasteners or tabs, can make the manipulation more difficult.

Learning is crucial for dexterous robotic manipulation in a less structured and uncertain disassembly environment. Although the kinematics and dynamics of manipulation have been widely studied in theory, in practice, standard rigid-body models and stiff control are most likely to fail due to inaccurate modeling due to unknown nonlinearity, unstructured human interaction, and state change or degradation of a robot (Siciliano and Khatib, 2016). Also, the solution to those complex kinematics, dynamics and path planning can be computationally intractable. ML can encapsulate these uncertainties and empower intelligent perception, adaptive motion control, and knowledge adaptation (Billard and Kragic, 2019; Karoly et al., 2021).

More specifically, ML can be applied to both forward modeling and inverse problem solving for manipulation purposes. Generally, as shown in Fig. 5 (a), a robot learning problem can typically be formulated as Markov decision processes, which are described by state, observation, action, transition function, a policy assigning an action to a transition, and cost or reward function for the policy (Siciliano and Khatib, 2016; Kroemer et al., 2019). The goal is to find the best policy to maximize the reward function, in other words, the best mapping from the observation space to the action space. For disassembly handling, the state of the disassembly robot and environment is observed by various sensors. The probabilistic transition function represents the potential effects of a specific handling operation. The typical output policy is the motion control strategy or parameters of the disassembly robots, e.g., the pose of the end effector with the highest probability of conducting a stable grasp or the toques of the robotic joint motors that lead to safe and smooth motion control.

Recently, self-supervision learning provided a simple way to autonomously find the best operation and control strategy. It can automatically collect unlabeled real-world data for learning, reducing the burden of expensive manual labeling and data library generation (Deng et al. 2019, Yan et al. 2020; Fang et al., 2020). Another way for policy learning is to learn the task from the demonstration, a.k.a. imitation learning (Lin et al.,2015; Xie et al. 2020). There is no need for manual modeling or designing the reward function. The system dynamics could be inversely learned. It is an attractive way for transferring the expert's disassembly skills to the robots. In addition to the policy learning, ML can also be engaged in learning the disassembly state change from

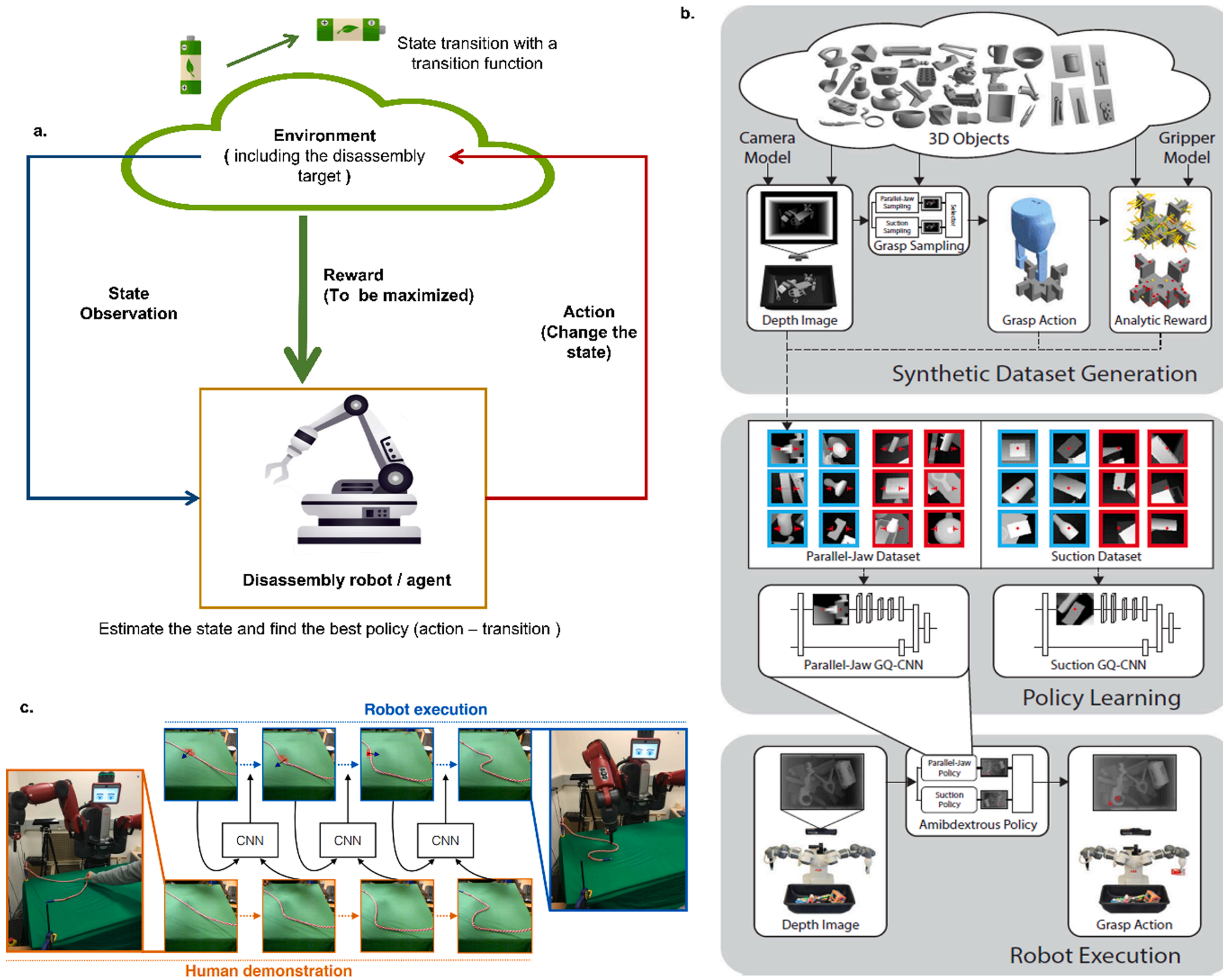


Fig. 5. Robotic learning for dexterous manipulation. a. Basic model of robotic learning; b. Dex-net 4.0 for universal and ambidextrous robotic grasping, reprinted from (Mahler et al., 2019); Rope manipulation by combined self-supervised learning and imitation learning, reprinted from (Nair et al., 2017).

observations or the transition model, such as manipulation success rate. For some complex scenarios, a mixed model is needed to extract the knowledge in a latent space and combine the forward and inverse learning to draw the solution (Nguyen-Tuong and Peters, 2011). Besides, learning-based models are also widely explored for the motion controller design at the fundamental device level, although this sub-topic is not the focus of this review.

Some intriguing advances in robotic manipulation of generic and deformable objects are very promising, that may benefit EV-LIB disassembly handling. Tremendous works developed DNNs for learning the handling pose, points, policy, and stability performance from the point cloud (Bui et al., 2020; Gualtieri et al., 2016), visual data (Deng et al., 2019; Saxena et al., 2008), videos (Yang et al., 2015), tactile feedback (Bekiroglu et al., 2011), and vision-tactile mixed perception data (Calandra et al., 2018; Zhang et al., 2017). Beyond the traditional vision capability, even hand-object interaction forces can be estimated from vision information by learning the mapping between high-level kinematic features and the manipulation forces using recurrent neural networks (RNN) (Pham et al., 2018). This would be useful for imitation learning and humanoid gripper design and control.

One latest DNN design for universal and ambidextrous robotic picks and grasps, named Dex-net 4.0, was trained and developed, reaching 95% reliability with 300 picks per hour (Fig. 5 (b)) (Mahler et al., 2019). This work is based on simulation-to-real learning. A large amount of synthetic data (5 million synthetic depth images) are generated by modeling and simulation. Domain randomization in object physics, sensing and control parameters are applied in the simulation to improve the robustness of the trained model. The major limitations are its high computation complexity in synthetic data generation and unavoidable simulation-to-reality gaps. The real disassembly environment could be complex and time-varying. The data distribution shifts of the real-world environment from the training dataset may reduce its reliability.

Another valuable progress is the deformable component grasping, which can handle and remove the cables and wires in an EV-LIB. For instance, rope manipulation was performed from vision images by learning the inverse dynamics model (Nair et al., 2017). Self-supervised learning and imitation are combined to achieve this learning task (Fig. 5 (c)). One latest work further demonstrates that cable sliding dynamics can be learned and solved to follow and manipulate the cable through real-time vision-based tactile feedback (She et al., 2019) (Fig. 2 (g2)). Learning-based tool manipulation is also investigated, but the overall success rate still heavily depends on the shape of the tool (Fang et al., 2020).

Despite immense advances, robotic manipulation is still generally much below human handling dexterity (Billard and Kragic, 2019; Caldera et al., 2018). A fully autonomous disassembly system with dexterous and humanoid robotic hands calls for more improvements in the design of intelligent hardware and algorithms. Multimodal learning, integration with analytical models, and perception fuse are promising attempts to improve intelligent manipulation (Lenz et al., 2015; Mahler et al., 2017).

4.4. Intelligent interaction and collaboration

Currently, fully autonomous disassembly without any human assistance is technically and economically impractical for high-quality EV-LIB recovery. Interaction and even collaboration with human workers, whatever actively or passively, is still necessary for a disassembly system.

4.4.1. Teleoperation disassembly

Teleoperation addresses the notorious safety concerns, and deals with EV-LIB disassembly in potentially protective environments. As mentioned in Section 2.1, many safety risks occur in the disassembly process of EV-LIB. Usually, qualified and well-trained employees and a specially designed disassembly environment are required to avoid accidents and damages (Fan et al., 2020). Even qualified workers with protective equipment are not one hundred percent safe. Moreover, some special disassembly requirements, such as disassembly in a heating system, freezing airs, or even solvent, prevent fine disassembly

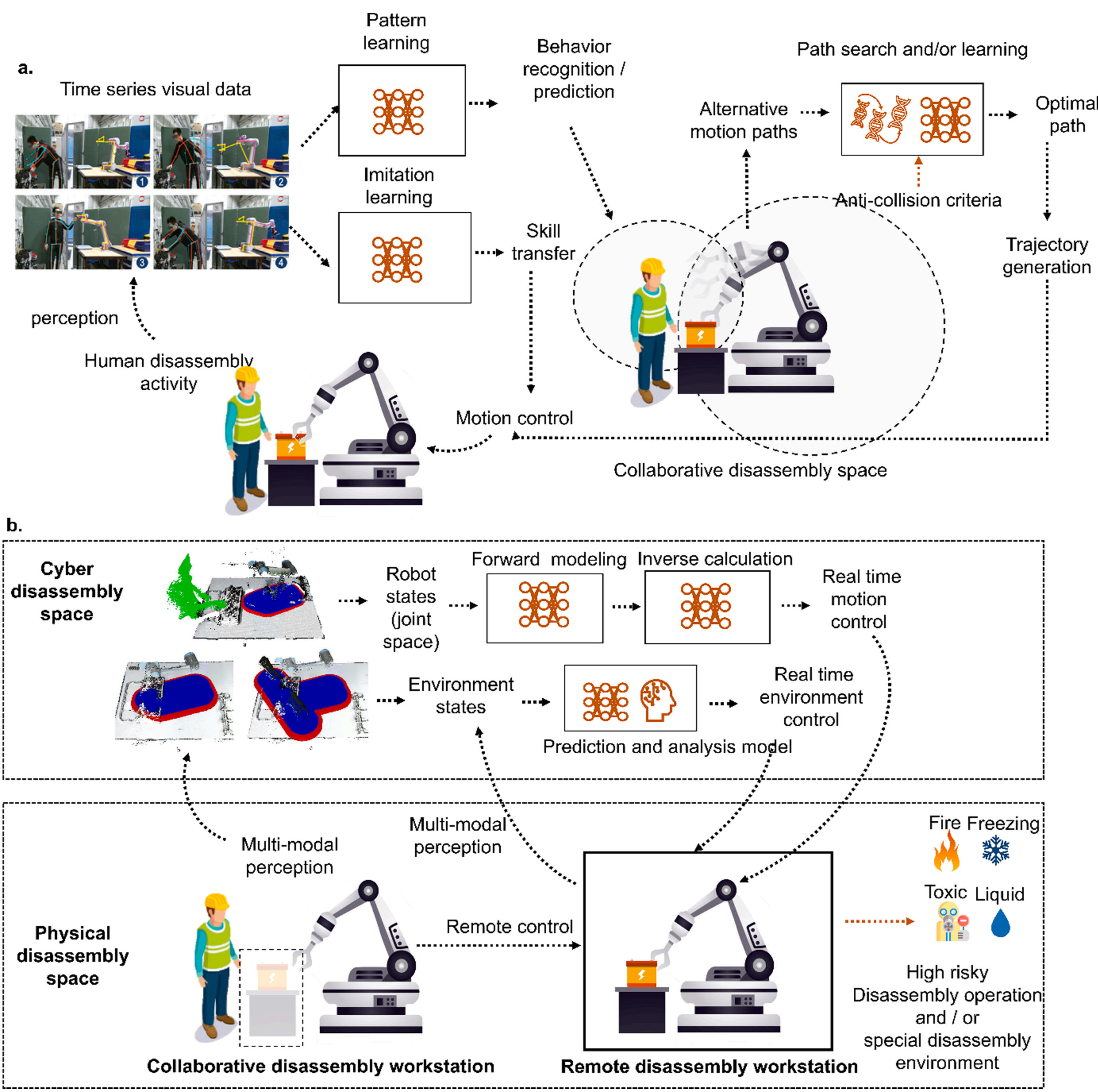


Fig. 6. Human-robot intelligent collaboration in EV-LIBs disassembly. (a) Human activity and behavior learning for human-robot collaborative disassembly. Time series visual data: reprinted from (Zhang et al., 2020b); (b) Remote disassembly collaboration based on digital twin. AR-based human-robot collaboration scenario in cyberspace: reprinted from (Hietanen et al., 2020).

operations, interaction, and control.

Intelligent teleoperation is a promising technology for handling disassembly tasks in hazardous or irregular environments. Telerobotic manipulation has contributed to many applications such as underwater tasks, space, and bomb disposal. Recently, increasing attention has been on intelligent surgical robots, showing convincing evidence of teleoperation's dexterity. Some latest researches on surgical robots further demonstrate the effectiveness of learning-based teleoperation in position estimation (Peng et al., 2019), tool identification (Su et al., 2019), and motion control (Kassahun et al., 2016; Shin et al., 2019; Li et al., 2017). These industrial applications indicate the potential of teleoperation for handling hazardous manufacturing environments.

Intelligent teleoperation disassembly can potentially be realized in three autonomy levels. The first option is to directly control and manipulate the robot to transfer the skills and complete disassembly tasks through intelligent wearable equipment and motion tracking (Lee et al., 2018; Bellitti et al., 2020). Ideally, it aims to possess human-level manipulation dexterity, whereas it is highly difficult, complex, and expensive for current industrial applications. Another way is remotely supervising the robot manipulation. One promising realization for such real-time remote control is based on a cyber-physics system (CPS) (Liu and Wang, 2020) (Fig. 6 (b)). Humans can lead through and interact with a disassembly robot in a safe area, while all the real-time motion states of this robot are monitored and estimated in cyberspace. Then, the kinematics and dynamics inverse problem will be solved to generate real-time motion command to control the remote disassembly robot in a hazardous environment. The third choice is shared remote control, under which the disassembly robot is controlled by both human command and its own cognitive decisions. Such robots can learn disassembly skills and plans from human demonstration and their process knowledge database to make autonomous operation decisions (Vongbunyong et al., 2015). DNN based imitation learning has demonstrated great potential in this mode for different manipulation tasks (Tung et al., 2020; Zhang et al., 2018). Intelligent methods have also been applied to handle the system uncertainties in a teleoperated system (Li and Su, 2013) or extract high-level kinematic patterns and infer the optimal action policy (Rakita et al., 2019). It is reasonable to expect intelligent teleoperation to bring safer and more efficient disassembly operations for EV-LIBs. Specific comparisons of these methods are provided in Table 4.

4.4.2. *Human-robot collaborative disassembly*

Intelligent human-robot collaborative disassembly (HRCD) is the most promising but also challenging mode for EV-LIBs disassembly and recovery (Yun et al., 2018). HRCD combines the human's high-level perception, dexterity, and intelligence with robots' strength, endurance, precision, and learning capability to achieve high-efficient, human-friendly and sustainable disassembly. From both technical and economic viewpoints, HRCD provides more flexibility and practical routes to realize intelligent disassembly as there are multiple modalities to implement HRCD. The robot can play an active or supportive role when working with human workers and conduct the disassembly task in a sequential(cooperation) or simultaneous (collaborative) way (Gualtieri et al., 2021; Wang et al., 2017).

Learning capability is undisputedly central to the HRCD system for dealing with complex tasks in a human-robot-LIB disassembly environment. Generally, intelligent capabilities contribute to the perception, cognition, decision-making, and execution in an HRCD system through fusing multimodal sensory data and learning task-oriented knowledge (Liu et al., 2019; Liu et al., 2018). To give an example, active and dynamic anti-collision is one crucial safety requirement to realizing both physical and mental seamless collaboration in completing disassembly tasks. To this end, it is necessary to recognize and predict human activity and behavior and plan the robotic motion trajectory. Recently, deep learning has attained increasing interest in addressing these two

Table 4
Typical intelligent methods for human-robot disassembly collaboration

Tasks	Methods	Advantages	Disadvantages	Ref.
Intelligent teleoperation	Direct remote control through wearable equipment	•High safety •Human handling dexterity •Capable of incorporating human perception and decisions	•Additional hardware system •High technology complexity •Not proven in industrial scenarios	(Lee et al., 2018) (Bellitti et al., 2020)
	CPS/DW based remote control	•High safety •Real time interaction •Capable of remote lead-through	•Additional CPS/DW system design •High technology complexity •High requirement for system integration and response time	(Liu and Wang, 2020)
	Deep learning based shared control	•High safety •Combined human commands/ demonstrations and robotic learning capability •Capable of handling system uncertainty and complex models	•Require sufficient training •Limited generalization capability	(Zhang et al., 2018) (Rakita et al., 2019) (Tung et al., 2020)
Human action recognition/ prediction for collaborative operation	RNN based prediction	Suitable for time-series data handling	•Require sufficient training and fine parameter tuning •Vanishing gradient (can be solved by LSTM, but not proven in industrial HRCD scenarios)	(Zhang et al., 2020b)
	DCNN based recognition	•Strong capability of handling nonlinear representation •Robust capability of extracting action features	•Require sufficient training and fine parameter tuning •Not capable of dealing with time-dependent data	(Wang et al., 2018)
Motion control for collision avoidance	Supervised learning	End-to-end one-shot generation of the collision-free path waypoints	•Require sufficient dataset generation and training •Require HRC space discretization	(Meziane et al., 2017)
	Deep RL	•Adaptive and autonomous sequential control and decision-making •Capable of handling uncertain HRCD environment	•Require expertise on reward function design •Slow iteration for large scale problems •No guarantee on stability and global optima	(Oliff et al., 2020) (Moreira et al., 2020)
	CPS/AR/VR	Real-time monitoring, evaluation and interaction	•Additional system investment •High requirement for system integration and response time	(Nikolakis et al., 2019) (Hietanen et al., 2020)

problems (Fig. 6 (a)). For human behavior prediction, RNN proves to be suitable to capture the patterns of time-dependent human motion series to predict their motion trajectory (Zhang et al., 2020b). A modified DCNN (AlexNet) was also adapted to recognize human actions associated with their context (Wang et al., 2018).

For the robotic motion trajectory, a supervised learning NN was proposed to help identify the optimal collision-free path for the robot motions in an end-to-end way (Meziane et al., 2017). However, this method can only generate the path waypoints based on the space discretization. Deep reinforcement learning was also applied for active robotic motion planning and control to align the robots' actions with their human colleagues (Oliff et al., 2020; Moreira et al., 2020). Another popular idea is to build a digital twin of the HRCD system to map the physical disassembly system into physic-informed digital models in cyberspace (Nikolakis et al., 2019). Then the simulation, safety evaluation, and control decision-making are conducted in cyberspace (Fig. 6 (b)). Meanwhile, emerging augmented reality and virtual reality technologies potentially provide more intuitive interaction for the human-robot collaboration (Hietanen et al., 2020). CPS or digital twin enables more efficient, user-friendly, and real-time control of the HRCD system. Multi-modal sensors can be applied to assess and even predict the states of not only the human workers and disassembly systems but also the disassembly environment (Liu et al., 2019). This is significant for ensuring safe disassembly. First, the disassembly activities and interactions of humans and robots can be monitored in a real-time way to avoid any harm from the robotic system to the humans. Second, all the disassembly equipment conditions and process information can be fused to make comprehensive risk assessments. Predictive protection and maintenance can be made to prevent the disassembly system from severe failure. Also, environmental indicators such as temperature, smog, humidity, air cleanliness, and quality, can be monitored and evaluated timely to avoid hazardous waste leakage and risky accidents. However, the implementation of the CPS-based HRCD is a very complex and systematic project, requiring multimodal perception fusion, high-speed and high throughput data processing, high-complexity modeling and visualization, and high-level system integration.

In addition to physical safety, psychological and cognitive ergonomics is also an essential requirement for HRCD (Gualtieri et al., 2021). For example, human workers' trust in their robot colleagues influences their cooperation efficiency. DNN's potential to extract the human behavior pattern can also investigate the human trust model in machines (Akash et al., 2018).

4.5. Beyond EOL: Intelligent design for disassembly

Design for disassembly (DFD) can significantly reduce the difficulty of the disassembly process and thus save the resource, energy, and cost, to promote the high-level circularity of EV-LIBs (Steward, 2020). Avoiding adhesive connections, using more removable fasteners, and replacing the liquid electrolyte are practical actions to improve the EV-LIB's disassemblability. The design of free-standing cathodes and anodes may not need the aluminum and copper current collectors, further simplifying the material classification process. Another intriguing option is designing an actively removable connection. Such connection components can change their morphology by triggering stimuli (e.g., heating) to proactively disconnect themselves, leading to non-destructive mass disassembly (Abuzied et al., 2020; Peeters, Vanegas, Dewulf and Duflou, 2017). One typical realization is using shape memory alloy/polymer; however, designing a safe triggering mechanism is challenging for EV-LIBs due to the thermal risks.

AI/ML can also potentially empower the eco-design of EV-LIBs. As shown in Fig. 7, AI could help predict the performance of a potential design or realize on-demand design through self-evolution. DFD knowledge clouds and tools can speed up the eco-design process and even assist in the joint design of the product and its disassembly system (Huang et al., 2017; Favi et al., 2016; Battaïa et al., 2018).

It is worth noting that ML has been widely used for energy material screening, structure-activity relationships modeling, and material property prediction (Liu et al., 2017; Li et al., 2020a; Liu et al., 2021; Chen et al., 2020ba; Chen et al., 2020cb; Morgan et al., 2022) (Fig.7 a-c). It is promising to investigate and design better electrode materials and electrolytes through robotic experiments and intelligent analysis (Dave et al., 2020; Allam et al., 2018; Takagishi et al., 2019). For instance, the evolving nature of the battery electrode microstructure was statistically examined through a Mask R-CNN (Jiang et al., 2020). On-demand inverse design of new battery material was also suggested by using generative DNNs (Bhowmik et al., 2019) and Bayesian optimization (Wang, Wang and Yang, 2020b). As one recognized technology trend, solid-state batteries without liquid electrolytes are extremely attractive for easy disassembly and recovery. ML has also contributed to the solid electrolyte (Li-ion conducting material) discovery (Ahmad et al., 2018; Hatakeyama-Sato et al., 2019; Sendek et al., 2018; Zhang et al., 2019) and lithium morphology tracking (Dixit et al., 2020).

The AI/ML methods for battery material design adopted in the above studies are summarized and compared in Table 5. In the near future, there are immense opportunities for AI to assist in designing and unlocking disassembly-friendly EV-LIBs through discovering new materials, structures and mechanisms.

5. Discussion

Section 3 and Section 4 addressed the research questions RQ1 and RQ2, respectively, by providing systematic review and analysis. This section contributes to answering RQ3: "What are the progress, opportunities, and challenges of EV-LIBs intelligent disassembly?"

5.1. AI/ML's value and opportunities

To further identify the contributions and progress of AI/ML methods for EV-LIB disassembly, Table 6 summarizes the scientific problems solved by the major intelligent disassembly methods reviewed in Section 4, along with their functional roles and technology maturity evaluations. Specific discussions are presented as follows.

5.1.1. Scientific and applied contributions

From the viewpoint of scientific contributions, the state-of-the-art review and Table 6 demonstrate AI's significant potential and value for tackling scientific problems in intelligent disassembly, particularly addressing forward modeling and inverse problem solving through learning. The existing studies have contributed a wide range of valuable models, methodologies, and knowledge to the research field of forward modeling and inverse problem solving through learning in disassembly. Fig. 8 concludes and illustrates these contributions of disassembly intelligence. In this framework, the forward problem considers learning a generalized mapping function from the state space into the objective space, where the state refers to the state of EV-LIBs, disassembly systems, or both. The objective is desired knowledge or performance. As listed in Table 6, current studies on EV-LIB state prognostics, disassembly object detection, human activities recognition and prediction, knowledge discovery and forward motion modeling contribute to this category. In reverse, all the disassembly decision-making problems that seek a desired state, strategy, or action by iterative learning are considered inverse-problem solving. Generally, the proposed models and methods in the review for planning, control, search, and optimization problems in intelligent disassembly contribute to this inverse problem. These inverse problems are usually notorious due to ill-posedness, where the solution may be non-unique. AI/ML methods have been proved effective for solving such problems.

From the perspective of applied contributions, AI/ML shows the power to address the five big challenges for EV-LIB disassembly presented in Section 3. Take the safety risk as an example. The current studies suggested various AI/ML methods to protect human health

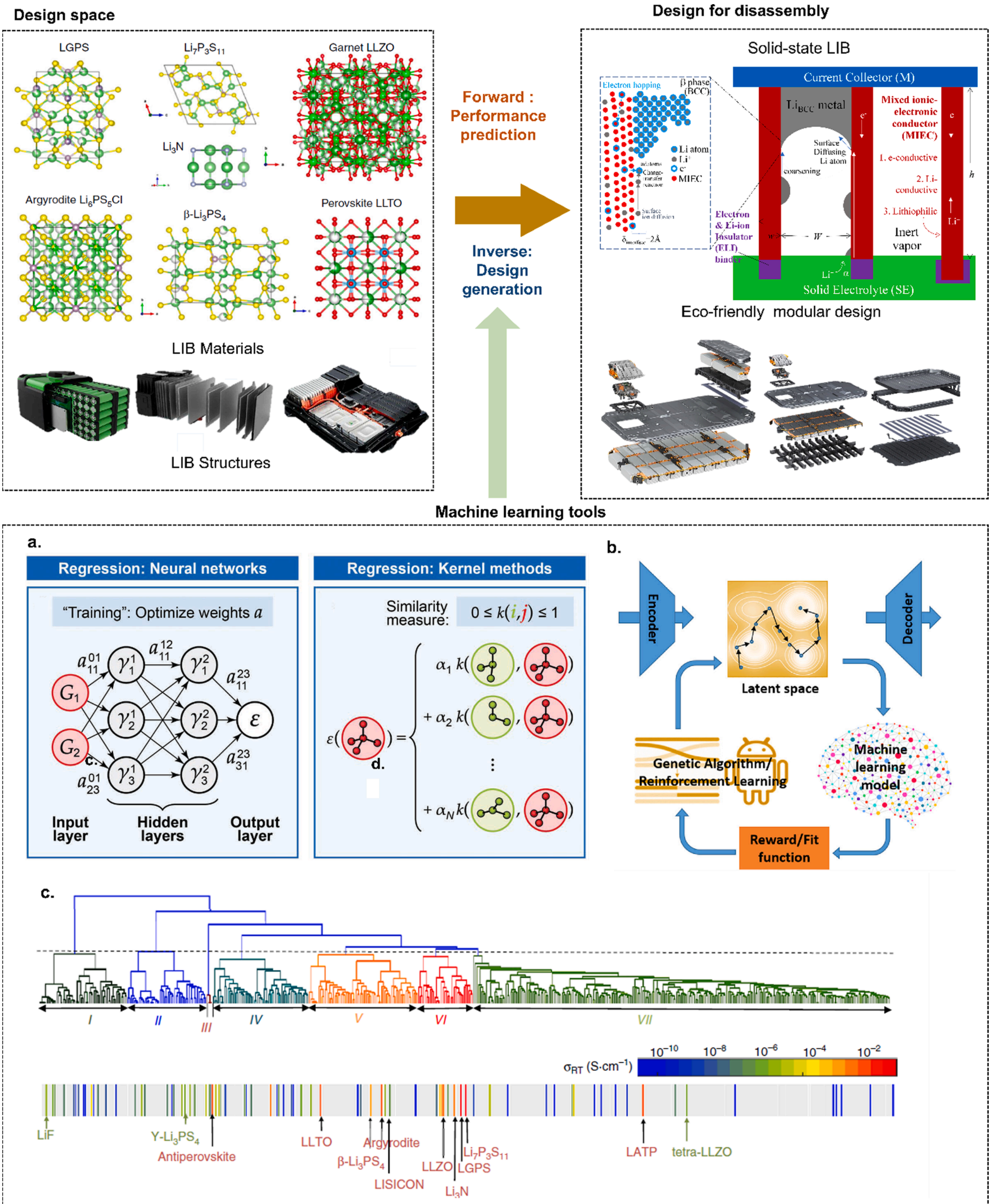


Fig. 7. Intelligent design of EV-LIB for easy and eco-friendly disassembly. Design space: LIB materials, reprinted from (Zhang et al., 2019); LIB structures, reprinted from (Yang et al., 2020). Machine learning tools for new battery material/structure design: a. Regression based methods, either neural networks or Kernel methods, have been widely used for material design. Reprinted from (Deringer et al., 2019). b. Machine learning combined with iterative genetic algorithms or reinforcement learning for battery inverse design. Reprinted from (Bhowmik et al., 2019). c. Unsupervised clustering for discovering new solid-state conducting material. Reprinted from (Zhang et al., 2019). Design for disassembly: All-solid-state LIB, reprinted from (Chen et al. 2020c). Modular design, reprinted from Audi e-tron Sportback 2021 (Audi, 2021a).

Table 5
Typical intelligent methods for new battery material discovery and design

Tasks	Methods	Advantages	Disadvantages	References
Property prediction and/or screening	NN for performance prediction and screening	•Strong capability of approximating nonlinear and black-box function •End-to-end learning and prediction •Capable of handling big data for fast and autonomous screening	•Require sufficient training and testing •No standard design of the NN •Dependent on the training data or simulation input •Lack of interpretability	(Ahmad et al. 2018) (Allam et al., 2018) (Hatakeyama-Sato et al., 2019)
	Clustering for screening	•Unsupervised learning, no need of labelled samples •No need of accurate property prediction •Fast screening for identifying the promising candidates	•Require sufficient training dataset •No guarantee of convergence	(Zhang et al., 2019)
	Robotic experiments	•High throughput experiments •Accurate analysis and assessment	•Additional system design and investment •High requirement on system autonomy level and reliability	(Burger et al., 2020) (Dave et al., 2020)
On-demand inverse design	Generative DNN	•Unsupervised learning, no need of labelled samples •Creative design by automated exploration	•Require expertise on training •No guarantee of stability	(Bhowmik et al., 2019)
	Bayesian optimization	•Capable of efficient exploring design space •Capable of handling black-box function regression	•High computation burden and intractable for high dimensional and large-scale datasets •Lack of parallelism •No guarantee of stability	(Wang et al., 2020a) (Takagishi et al., 2019)
Mechanism investigation	R-CNN based statistical analysis	•Automated, fast and accurate identification and segmentation of particles through image learning •Easy to implement	•Require sufficient training •Slow learning speed	(Jiang et al., 2020)

during the EV-LIB disassembly from five aspects. The first strategy is reducing the involvement of human workers by improving the autonomy level of robotic handling and disassembly. All the intelligent methods for autonomous checking, testing, sorting, target detection, and robotic separation/manipulation contribute to this safety goal. Second, teleoperation disassembly is suggested for allowing the workers to conduct disassembly operations without direct contact with those risky operations, environments, and toxic substances. Further, in a human-robot collaborative disassembly system, multi-modal perception technologies combined with intelligent algorithms are suggested to better monitor and plan all the disassembly activities and interactions, avoiding the potential harm to humans. More importantly, as presented in Section 4.4.2, real-time monitoring and predictive control of the hazardous disassembly environment are practically based on the IoT and CPS systems. Such a smart disassembly factory will minimize the risk of accidents. Finally, the ultimate solution is reducing the use of potentially hazardous materials in the EV-LIB design. Various intelligent design methods can also contribute to such eco-designs for green disassembly, as discussed in Section 4.5. As for addressing the variety and uncertainty challenges, AI/ML has also been applied to enhance the adaptiveness of EV-LIB disassembly systems through fused perception, dynamic response and decision-making, and flexible robotic handling. More detailed intelligent solutions to those disassembly challenges are summarized in Table 7.

5.1.2. *Technology readiness and opportunities*

From the perspective of technology readiness level (TRL), intelligent EV-LIB disassembly is still at an early stage. Most of the current intelligent disassembly methods are still at the conceptualization and lab level. Some of them have not been validated in the EV-LIB disassembly scenarios and relevant environments. To better evaluate their potentials for the EV-LIB disassembly industry, a simple TRL evaluation is given in this paper to provide a general estimation of if an AI/ML approach can be applied or transferred to the EV-LIB disassembly. The proposed TRL evaluation center on EV-LIB disassembly applications with six levels as follows:

- TRL1: Conceptual solutions, not applied or validated in any field of manufacturing industry;
- TRL2: Conceptual solutions for EV-LIBs disassembly, but lab or prototype level studies have been reported in other manufacturing engineering areas;
- TRL3: Conceptual solutions for EV-LIBs disassembly, but industrial applications have been reported in other manufacturing engineering areas;
- TRL4: Lab or prototype level solutions for both EV-LIBs disassembly and other manufacturing engineering areas;
- TRL5: Lab or prototype level solutions for EV-LIBs disassembly, but industrial applications have been reported in other manufacturing engineering areas.
- TRL6: Industrial applications have been reported in the EV-LIBs disassembly industry.

The evaluation results are shown in the last column in Table 6. The surveys or research evidence supporting the grading are also provided. As there is no mature scaled application of intelligent disassembly in the current EV-LIB recovery industry, the TRL 6 application remains vacant.

The most widely studied and close-to-application topic is the EV-LIB state estimation and prognostics (TRL5). Numerous studies have contributed to this topic and provided lab-level validations (Hu et al. 2020; Ng et al., 2020). Meanwhile, such prognostics and health management technologies have already been applied for providing intelligent maintenance services in other manufacturing industries, such as the aero-engine industry. It is reasonable to expect intelligent prognostic technologies are applied to the real-world retired EV-LIB management as an important decision support tool. Another TRL5 application is intelligent disassembly decision-making. Intelligent decision-making, planning, and scheduling methodologies have been successfully utilized in many manufacturing and logistics practices. Those generic decision-making/planning models and approaches can be easily transferred and applied to EV-LIB disassembly as the nature and structure of the optimization problem keep unchanged. Intelligent object detection is also a promising point. A prototype-level detection unit has been proposed for EV-LIB disassembly (Poschmann et al., 2021). As computer vision based detection has been widely used in various industries and constantly improving, it is feasible to put intelligent EV-LIB detection into industrial disassembly scenarios in the near future. Despite the great potential of these TRL5 technologies, more applied research is needed to prove their effectiveness in EV-LIB disassembly.

Table 6
The roles and potentials of AI/ML methods for EV-LIBs intelligent disassembly

Disassembly Process	Intelligence problem	Input X	Output Y	What to learn (mapping f)	AI's role	TRL*
Pre-processing: Check /testing /sorting	Health state prognostics	Condition monitoring data series	Health state indicators	Implicit degradation mechanism	Approximator /predictor	●●●●●○ (Hu et al. 2020) (Ng et al. 2020)
	Pack/module/cell detection	Sensory data, typically visual data	Model type	Geometric /physics features	Classifier /cluster	●●●●●○ (Poschmann et al., 2021) (Choux et al., 2021)
	Quality classification /grading	Experimental and/or testing data	Class/Quality grade	Physics /chemical properties	Classifier /cluster	●●●○○○ (Paul 2020) (Lai et al., 2021)
Disassembly target detection	Component-level object detection	Sensory data, typically visual and force data	Component type, property, state and localization	Geometric /physics features	Classifier /discoverer	●●●●●○ (Poschmann et al., 2021) (Choux et al., 2021)
Separation Process optimization	Abnormal operation detection	Sensory data of separation process, typically visual and force data	Disassembly operation state	Disassembly operation features	Classifier /cluster	●●●○○○ (Barbariol et al., 2022)
	Parameter optimization	ELV-LIB component model and state	Optimal process parameter	Correlation between process parameter and disassembly effects	Optimizer /discover	●●●○○○ (Rao et al., 2017) (Tercan et al., 2017) (Singh et al., 2021)
Robotic dexterous Handling	Motion modeling and control	Sensory data of handling operation, typically visual and force data	Optimal action policy (control parameters)	Kinematics, dynamics and their inverse solution	Approximator/ discover /optimizer	●●○○○○ (Billard and Kragic, 2019
Human-robot interaction /collaboration	Human behavior recognition and prediction	Visual data series of human activities, usually RGB-D data	Human motion trajectory	Implicit human behavior features and pattern	Approximator /discover /predictor	●●○○○○ (Zhang et al., 2020b)
	Motion planning for collision avoidance	Human and robot motion space and current states	Optimal motion path	Correlation between motion path and collision-related optimization criteria	Planner /Optimizer	●●○○○○ (Oliff et al., 2020) (Meziane et al., 2017)
Decision making /Planning /scheduling	Combinatorial optimization	Information w.r.t LIB model, return flow, disassembly tasks and system capacity	Optimal disassembly plan	Correlation between disassembly plan and operation optimization criteria	Planner /Optimizer	●●●●●○ (Poschmann et al., 2021) (C3. AI, 2021)
Battery material design	Battery material property prediction	Candidate material structure	Material property	Correlation between microstructure and property	Approximator /discover /predictor	●●●●○○ (Chen et al., 2020b) (Liu et al., 2021)
	Generative design	Candidate design space	Optimal design	Correlation between the design pattern and design criteria	Discover /optimizer	●●●●○○ (Bhowmik et al., 2019)

* TRL: Technology readiness level. ●○○○○○: Pure conceptual solutions; ●●○○○○: Conceptual solutions for EV-LIBs disassembly, but lab or prototype level in other manufacturing industries; ●●●○○○: Conceptual solutions for EV-LIBs disassembly, but applied in other manufacturing industries; ●●●●○○: Lab or prototype level for all possible manufacturing industries; ●●●●●○: Lab or prototype level for EV-LIBs disassembly, but applied in other manufacturing industries; ●●●●●●: Applied in EV-LIB disassembly industry.

Substantial research efforts are still required for promoting the intelligent EV-LIB disassembly into reality. The results also indicate some other research opportunities including but not limited to:

1) *Intelligent high-throughput testing.* Non-destructive testing is still necessary and important for accurate performance characterization of retired EV-LIBs. Particularly, for mass disassembly and recovery, fast, reliable, and smart batch testing from the pack level to the cell level requires both academic innovations and engineering developments. How to integrate AI/ML's prediction, physics modeling and robotic non-destructive testing to achieve more intelligent performance characterization is a fascinating challenge.

2) *Green and smart disassembly operation.* More nondestructive and simultaneous disassembly processes with optimized energy performances need to be explored, particularly for adhesive and soldering joints. Even destructive disassembly requires more fundamental research to revolutionize or optimize the processing. Meanwhile, the disassembly process management requires more intelligent uncertainty management and control. More future works are expected to study how to detect the defective components and abnormal conditions in an unstructured disassembly environment.

3) *Human-robot integration system.* To handle complex tasks like EV-LIB disassembly, human-robot collaborative disassembly should move to better share and integrate the capability of perception,

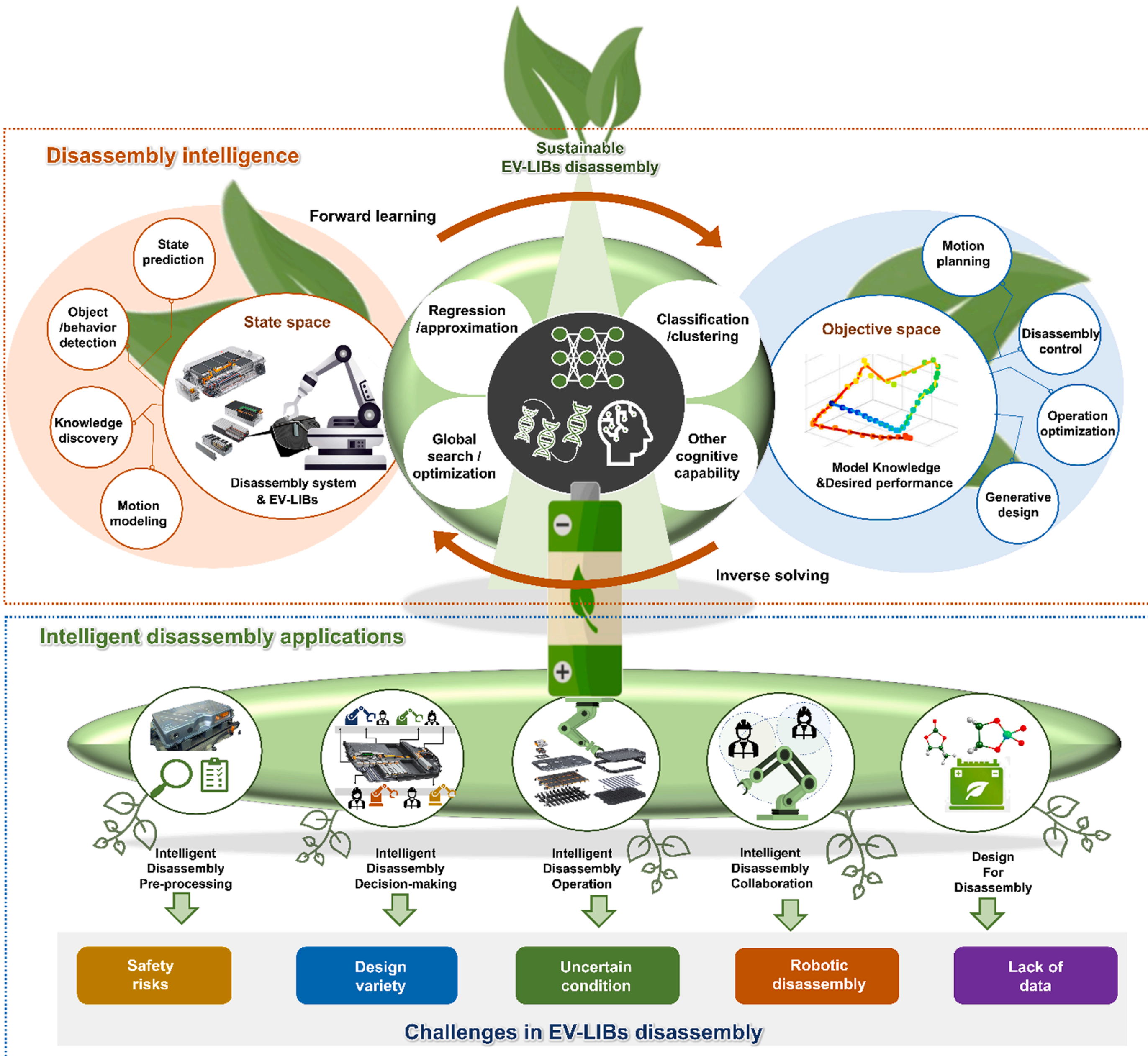


Fig. 8. Scientific and applied contributions of AI/ML for EV-LIBs disassembly. The EV-LIB pack/module/cell pictures are reprinted from (Yang et al., 2020), (Rallo et al., 2020), (Audi, 2021a); The desired performance curve showing a human-robot collaborative disassembly motion trace is adapted from (Liu et al., 2019);

learning, execution, and decision-making from both humans and robots. It is exciting to integrate emerging Industrial 4.0 technologies such as AR/VR, wearable sensing devices and even brain-machine interfaces into the collaborative disassembly system. The question is how to make full advantage of these technology elements to boost the disassembly performance.

4) *Safety engineering for EV-LIB disassembly*. Some practical requirements propose interesting research questions on how to better protect human health during disassembly. Due to EV-LIB's hazardous characteristics, Personal Protective Equipment, e.g., safety coats, glasses and gloves, are needed to protect humans from the contact of acid and alkali chemicals, such as HF and NaOH. Also, the disassembly equipment and even job shop require special safety design such as a negative pressure room for preventing toxic gases. In addition, the waste treatment systems are also significant to reduce the pollution during the disassembly process, such as gas purification and water recycling/treatment systems. How to integrate the intelligent disassembly system with these safety systems? Can AI/ML assist in the design and control of them? All these remain to be explored.

5.2. Application challenges

This sub-section discusses the pitfalls and challenges of EV-LIB intelligent disassembly to provide insights into the system implementation.

5.2.1. AI/ML's pitfalls

Despite the popularity of AI and its surging applications in diverse areas, there is still a need to see both the hope and hype aspects in this AI era. Can AI always contribute to sustainable disassembly and recovery? This is still an open question. There is one premise: can we always trust

Table 7
Intelligent solutions to addressing EV-LIB disassembly challenges

Challenges	Intelligent requirements	Intelligent solutions
Safety risks	•Autonomous disassembly process	Section 4.1: Autonomous checking, testing, and sorting
		Section 4.3.1: Intelligent target detection
		Section 4.3.2/4.3.3: Robotic separation and manipulation
	•Remote control and operation	Section 4.4.1: Teleoperation by direct/indirect/shared control
	•Active collision avoidance	Section 4.4.2: Intelligent recognition and prediction of human activities, intelligent motion planning
	•Environment monitoring and control	Section 4.4.2: Multimodal CPS based risk prevention
	•Green and hazard-free LIB design	Section 4.5: Intelligent eco-design of new battery materials
Design variety	•Model recognition and identification	Section 4.1: Intelligent recognition
	•High-flexibility and adaptive disassembly capability	Section 4.2: Adaptive and flexible disassembly planning
		Section 4.3.1: Intelligent target detection
		Section 4.3.3: Generic and dexterous robotic manipulation
	•New design of standard EV-LIBs	Section 4.5: Intelligent eco-design methods
Uncertain conditions	•Uncertainty perception and estimation	Section 4.1: Intelligent recognition and EV-LIB state prognostics
		Section 4.3.1: Intelligent target detection and abnormal detection
		Section 4.3.2: Disassembly effects prediction
	•Human-robot interaction	Section 4.4.1: Shared control with robot's learning capability
		Section 4.4.2: Human perception + multimodal sensors
	•Uncertainty response capability	Section 4.3.2: Intelligent process optimization
		Section 4.3.3: Flexible manipulation capability
		Section 4.2: Context-aware and dynamic planning/scheduling
Difficult for robotic disassembly	•Separation process optimization	Section 4.3.2: Versatile and efficient disassembly functions/tools
	•Dexterous manipulation	Section 4.3.3: Robotic manipulation of deformable components
	•Human-robot interaction and collaboration	Section 4.4: Incorporate human's manipulation flexibility and dexterity
	•Design for easy disassembly	Section 4.5: Intelligent eco-design for active or easy disassembly
Lack of data	•Intelligent identification and sharing	Section 4.1: Intelligent labeling with IoT system
	•High-throughput testing	Section 4.1: Robotic testing
	•All-stakeholder cooperation	Section 4.2: Cloud disassembly
	•Human-robot collaboration	Section 4.4: Incorporate human's manipulation perception and flexibility

AI during the disassembly process considering its accuracy and transferrability? Prediction performance research shows that pure ML methods and their combination can also perform poorer than traditional time series methods for some tasks (Makridakis et al., 2020). Not to mention that there are various widely-recognized issues regarding the application of AI, such as training data quality and quantity, high computational burden, low interpretability, overfitting, reproducibility and repetitive precision issues, and bias issues, to name a few (Belthangady and Royer, 2019; Berecibar et al., 2016). Even though the accuracy is acceptable, potential overestimation or underestimation can result in additional environmental burden, treatment cost, and even safety risks. In section 4, the detailed technical drawbacks of various AI/ML methods are reviewed in Table 1-5. This section highlights three common problems in AI/ML application and implementation as follows.

1) *Training data acquisition.* There is no doubt that most of the AI/ML methods depend on the training datasets. In practice, data generation, recording and availability could be a big challenge. As mentioned in Section 4.1, today's BMS still cannot provide condition monitoring data for all the individual LIB cells. Tedious and time-consuming experiments are still required for data collection, not to mention manual labeling for some supervised learning cases. Similarly, robotic learning also needs to collect the experimental data for training the model, even in a self-supervised way. In addition to the data availability issue, data quality is a big problem. For instance, modeling and simulation may be one option for efficient data generation. However, imprecise physical models cause the simulation-to-reality gaps and even mislead the model training. From the practical view, how to obtain appropriate training data is an important question to answer before implementing AI/ML methods. The practitioners should carefully estimate the cost and quality of dataset collection or generation. The open database development over the EV-LIB supply chain can help with the industrial big data training for AL/ML implementations. Some general-purpose open databases and datasets for material development, object detection, and LIB lifetime prognostics have already been built (Liu et al., 2021; Zhao et al., 2019; Hu et al., 2020). Nevertheless, there is a need to construct datasets for specific EV-LIB disassembly scenarios to improve the training quality and AI/ML's performance. Another option is to determine more effective ways to combine multidisciplinary simulation and experiments. Hybrid data integration and learning model design are then needed.

2) *Performance reliability*. The performance (e.g., prediction accuracy) of AI/ML models is usually highly case-dependent and sensitive to the training dataset and learning strategies. In section 4.1, the recognition accuracy of a CNN-based detection model reaches 90%-97% for WEEE products. However, in Section 4.3.1, the accuracy of the CNN-based detection model for EV-LIB screws is down to 73.71%. Similarly, the iterative global search approaches also usually have convergence and local-optima problems for different optimization scenarios. It is very difficult to design or identify a one-fit-all model. For learning-based methods, what is worse is that real-world disassembly scenarios are likely to be different from the training dataset. The distribution shifts or even out-of-distribution data input may further affect the AI model's performance. Therefore, the premise of AI's capability to handle disassembly uncertainties is ensuring enough robustness of these AI models by sufficient and appropriate training, avoiding bias and overfitting. However, it is usually hard to identify the amount of training data and time required for a specific problem. The trial-and-error requirements increase the difficulty to control the training cost. In disassembly practice, the practitioners should examine the performance reliability and repetitive precision of their AI model and system. The performance tolerances for different disassembly tasks are also needed to be carefully estimated. Risky disassembly operations have no tolerance for decision mistakes that harm human health and safety. There might also be ethical and/or legal implications if an accident or severe pollution happens due to any AI's reliability problems.

3) *System Security*. The EV-LIB intelligent disassembly system is a highly heterogeneous and complex AI system including various hardware and software components. The system also faces different security threats from natural disasters, hardware degradation and errors, power failure, environmental variations, human operation

mistakes, and even cyber attacks. How to protect the data, process, system and facility security of AI systems is becoming a common challenge. These issues should be well considered and addressed in the design, employment and management of an EV-LIB intelligent disassembly system. First, the system should take into account fault-, disaster- and accident tolerance. Reliability analysis, assignment and testing should be conducted to achieve robust system design. All the facilities should be well protected from any potential natural disasters, e.g. fire, flood and storm, and environmental disturbances. Uninterruptible power supply and application service should be implemented for the key functional systems. A complete, practical and economic disaster recovery plan, such as data backup or dual data center, should be built to minimize the loss in some extreme cases. Second, all the data, models and algorithms should be well tested to ensure their robustness to any potential attacks. Various defense approaches can be utilized to prevent the AI system from data poisoning, backdoor attacks, adversarial attacks, model theft and sensitive data recovery (Xue et al., 2020; Shafique et al., 2020). Further, during the system operation, prognostic and health management systems for the AI equipment and facilities themselves are necessary. Multiple and even redundant online anomaly detection systems can be employed to protect the key functional equipment and conduct essential preventive maintenance. In addition, a complete operation and management protocol should be made and rigidly executed to minimize the risk due to human operation mistakes.

5.2.2. Sustainability considerations

EV-LIB intelligent disassembly should not contribute to a biased “sustainability” but take holistic sustainability into account (Li, Barwood and Rahimifard, 2019a). However, there are some contradictions in the implementation of EV-LIB intelligent disassembly. A systematic and multi-criteria sustainable benefits assessment should be conducted to draw the business plan considering the following issues.

First, economic investment and cost is not a trivial decision factor in practice. The direct hardware cost for today’s generic robots and automation equipment is affordable for most companies. The payback period is estimated to be around three years for an initial investment of 0.2 million euros for a cobot disassembly system (Blömeke et al., 2020). However, some customized design and development costs cannot be ignored. High-level autonomy may involve customized AI system, control systems, and cloud/fog/edge computing systems. Their design cost is highly case-dependent. In addition, the training, deployment, and maintenance of multiple AI systems could also be highly costly.

Second, disassembly and recovery revenues also depend on multiple factors. The chemical compositions of EV-LIBs are crucial because less valuable materials and elements will reduce the economic motivation for recycling. The completeness of the reverse logistic system and the maturity of the secondary market also matter. They affect the amount and stability of the retired EV-LIBs return flow and demands for disassembly and recovery. Also, different disassembly business modes lead to different intelligent requirements and costs. For centered disassembly, collection and logistics costs for EOL returns from the distributed reverse supply chain are also needed to consider. In addition, the number of EV-LIB model types to be disassembled also affects the requirements for system complexity and flexibility, and thus the investment.

Thirdly, the potential pollution and carbon footprints of the disassembly process and system, including the AI systems, should also be examined. A recent survey shows that even one single complex AI model training can cause terrible carbon emissions (Strubell et al., 2020). Now sustainable AI and green computing with carbon footprint tracking are gaining increasing attention (Anthony et al., 2020; Henderson et al., 2020). The sustainable design of the intelligent disassembly system requires the assessment and auditing of its lifecycle impacts. The carbon emission should be monitored and reported during the operation to optimize its energy performance for meeting the environmental sustainability goal.

Last but not least is the social sustainability of intelligent disassembly. This aspect is, to some extent, less discussed in the disassembly industry. “Replacing the human by robot” is motivated by the fact that the labor costs are increasing while the labor population is decreasing in many regions. However, the practical situations and their differences in underdeveloped, developing, and developed regions should also be examined. In a short-term view, if eliminating the safety risks, manual disassembly can create more labor-intensive job opportunities right now, given the present already-significant flux of retired EVs. On the other side, autonomous disassembly design, development, operation, and maintenance bring knowledge-intensive job creations. In short and medium terms, technology updates and advances should release the workers from heavy and risky tasks but not reduce the job opportunities. That is also one reason why human-robot collaborative disassembly is currently more attractive. Nevertheless, it is well believed that AI and robots will play more active roles in the disassembly and leave high-level decisions to humans. In the long term, the realization of fully autonomous disassembly requires more skilled workers on AI and robotic systems. Along with the technical progress, labor training is also critical to match the new skill requirements toward intelligent disassembly.

AI is not the universal key to all the current locks for sustainable disassembly and recovery. The final benefit of intelligent disassembly is not a simple addition sum. The sustainability performance should be assessed to ensure the match between an AI/ML system and a specific disassembly concern. The urgency for addressing intelligent and sustainable EV-LIBs disassembly in a holistic manner requires systems thinking in developing solutions. It is necessary for us to change the traditional tradeoff view to the value creation/co-creation view through innovations.

6. Conclusion

This paper provides a state-of-the-art review and forward-looking perspective of EV-LIB intelligent disassembly. The contributions of this work include three aspects:

1) The value of AI’s application in EV-LIB disassembly is evaluated and confirmed through a systematic review. The review shows that AI could benefit the whole EV-LIB disassembly process to achieve a sustainable circular economy for the EV-LIB industry. The most attractive value of AI lies in its ability to address the safety, variety, and uncertainty issues in EV-LIB disassembly. Accordingly, it can enhance disassembly efficiency and adaptiveness as well as reduce pollutions and hazards, while improving the profit.

2) The opportunities and challenges of EV-LIBs intelligent disassembly are identified and discussed. The progress of current intelligent methods is assessed to point out directions for future research and development. This review indicates that EV-LIB state prognostics, disassembly planning/decision-making as well as target detection are currently promising areas to move toward the intelligent era soon. The challenges also exist in realizing extensive autonomy in EV-LIB disassembly due to AI’s inherent shortcomings, mechanical and chemical complexities, and sustainable benefits concerns.

3) This paper also provides practical insights and forward-looking perspectives to boost EV-LIB intelligent disassembly. The pros and cons of the primary intelligent methods in this area are analyzed and compared. The results suggest that there is no free lunch for the AI method selection. To address this challenge, this work draws an overall map to direct how intelligent methodology and techniques can be selected and applied to the EV-LIBs disassembly. Also, remote human-robot collaboration combined with learning capability is suggested as the most practical way to address the safety and uncertainty issues while achieving TBL sustainability.

Advancing fully autonomous and intelligent disassembly of EV-LIBs is undoubtedly a forward-looking goal from the long-term perspective. It is an endless pursuit to optimize the disassembly technologies in preprocessing, detection, separation, manipulation, interaction, and waste management. Intelligent disassembly of EV-LIBs represents a promising means in improving the triple bottom line performance sustainability. Moreover, not limited to the spent EV-LIBs, our work also provides generic insights for other disassembly activities and systems.

One limitation of this research is that the review is mostly based on academic literature. Further investigations can be conducted to collect more industrial cases and expert opinions to further enrich the practical insights. Second, as intelligent disassembly involves a wide range of technologies at different levels, this review provides an overall roadmap and highlights the latest and the most promising areas based on the obtained materials. Future studies can deepen the analysis and further detail the roadmap for each disassembly process. Another direction to extend this study is to examine the AI/ML potentials for the after-disassembly recovery processes to achieve intelligent materials and chemicals recovery and recycling.

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.

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