

Robotic Autonomous Disassembly System for Automotive Power Battery Remanufacturing



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Abstract The remanufacturing of spent power batteries (SPBs) refers to a series of processes including inspection, disassembly, repair, reassembly, and testing for electric vehicle power batteries that have been used and reached the end of their original service life. This process aims to restore the batteries to the performance standards of new batteries, thereby extending their service life and achieving sustainable development. Using NIO Inc. as an example, we analyzed their energy service system and discussed the necessity of disassembling SPBs. In China, the development of SPB disassembly lines has evolved from manual disassembly on industrial assembly lines to refined disassembly and is now upgrading towards flexible, mixed-flow, and intelligent disassembly. To address this challenge, we have designed an intelligent robotic disassembly system based on NeuroSymbolic Artificial Intelligence. This system is built upon digital twin technology, forming a flexible mixed-flow disassembly solution capable of adapting to various demands. Through the ‘cloud-edge-client’ system, we have achieved real-time decision support, planning, and dynamic configuration and optimization of the disassembly process. This ensures the autonomy and efficiency of the disassembly operations. To tackle dynamic environments, complex scenarios, and unstructured tasks, we have developed and deployed an autonomous mobile manipulation robot named BEAM (Battery disassembly AMmr) for battery disassembly within the disassembly system. The introduction of BEAM has not only enhanced the intelligence level of the remanufacturing process but also propelled the entire remanufacturing industry towards higher quality and greater efficiency.

Keywords Spent power battery · Disassembly for remanufacturing · NeuroSymbolic AI · Cloud–Edge–Client architecture

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1 Introduction

1.1 The Rapid Growth and Future Vision of the Electric Vehicle Industry

Transportation-related carbon emissions account for approximately one-quarter of global energy-related carbon emissions [1]. Decarbonizing the transportation sector is a critical component in achieving global sustainable development goals and addressing climate change. The transition from internal combustion engines to electric vehicles is one of the most evident and direct pathways in the transformation of transportation energy. By the end of 2023, the penetration rate of new energy passenger vehicles in China reached 40.61%, with a national stock of 20.41 million new energy passenger vehicles [2]. Globally, electric vehicle sales and penetration rates are also steadily increasing within foreseeable bounds [3], marking the rapid and robust development of the electric vehicle industry.

1.2 Power Battery Life and Decommissioning Issues

As the core components of new energy vehicles, power batteries have a certain calendar life, which is the period from production until performance degrades to an unacceptable level. Additionally, the cycle life of the battery, which refers to the number of charge–discharge cycles it can endure, is another crucial indicator for measuring its service life [4, 5]. Currently, the average warranty period for power batteries in the industry is 8 years, which is significantly shorter than the normal lifespan of vehicles. The frequent occurrence of the “mismatch in lifespans between the vehicle and the battery” problem forces users to bear the high replacement costs due to battery degradation. This undoubtedly reduces the residual value of vehicles and increases maintenance costs [6]. Therefore, it is imperative to develop low-cost, environmentally friendly, and economically beneficial methods for handling spent power batteries (SPBs) [7].

The handling of SPBs can be categorized into cascade utilization, recycling, and remanufacturing. Remanufacturing involves inspecting, disassembling, repairing, reassembling, and testing SPBs to restore them to the performance standards of new batteries. Therefore, the effective disassembly of SPBs has become a critical foundational step in the entire remanufacturing process.

1.3 Autonomous Disassembly of Robots for Remanufacturing

Currently, the disassembly of SPBs primarily relies on manual operations assisted by mechanical tools. While this method can address diverse disassembly needs and

complex processes [8], it still faces challenges in mitigating chemical and electrical safety risks. The design of vision-based intelligent systems can more efficiently identify disassembly targets, while the targeted design of battery disassembly task planners offers new avenues for the research of fully automated battery disassembly robots [9]. Some studies also attempted to use more effective actuators to expand the range of manipulable objects [10, 11]. However, when it comes to planning issues, it is difficult to avoid pre-programmed methods, which undoubtedly limit the robot's ability to adapt to different dynamic scenarios during the disassembly process [12]. Therefore, an intelligent system for efficient disassembly of SPBs has yet to be investigated.

1.4 NeuroSymbolic AI for Task and Motion Planning

To better address pre-programming challenges, a promising approach is the use of NeuroSymbolic Artificial Intelligence (NeuroSymbolic AI), often regarded as the third generation of artificial intelligence [13]. It integrates high-level reasoning, achieved through logical systems, with lower-level perceptual abilities, achieved through probabilistic learning. At the high level, it performs knowledge-based logical reasoning, while at the lower level, it handles perception, control, and other tasks through probabilistic learning. These two levels work together to accomplish complex tasks. This technology has yielded significant results in many fields [14, 15]. For example, the introduction of NeuroSymbolic AI can effectively solve the motion planning problem of mobile robots involving temporal objectives [16] or extract task rules in the absence of explicitly labeled supervision [17]. The success of this technology across various fields stems from the use of neural networks, which provide flexibility, robustness, and scalability, combined with symbolic systems that offer interpretability, trustworthiness, and data efficiency [18], making it widely applicable to reasoning and learning tasks across multiple domains [19].

1.5 Content and Contribution of This Article

The remainder of this paper is structured as follows. Chapter 2 uses NIO Inc. (NIO) as a case study to discuss its energy service system and the technical challenges encountered in the remanufacturing of power batteries. Chapter 3 proposes a NeuroSymbolic based robotic autonomous disassembly system to address these real-world challenges. It is efficiently deployed through a Cloud-Edge-Client (CEC) system and safeguarded by an interactive digital twin system for high efficiency and safety. Chapter 4 provides a broader perspective on the future of power battery remanufacturing.

The main contributions of this paper are as follows:

- (1) Using NIO as an example, we analyze the current energy service system and modes of new energy vehicles, discussing the necessity of SPBs remanufacturing.
- (2) We design a NeuroSymbolic based robotic autonomous disassembly system, achieving robust autonomous disassembly of SPBs, and efficiently deployed by using a CEC architecture.
- (3) We developed an interactive digital twin system to enhance the efficiency and safety of the disassembly process.

2 Battery Rental Exchange Modes and Power Battery Remanufacturing

2.1 Battery Rental Exchange Mode

In the traditional automotive sales model, manufacturers often focus on the production process while paying insufficient attention to vehicle recycling and remanufacturing. Although some manufacturers have engaged in design for remanufacturing, they often struggle to achieve significant economic benefits. With the rapid development of the electric vehicle industry, manufacturers are becoming more attentive to user experience, particularly regarding the lifespan of power batteries. To extend the lifespan of power batteries and create more competitive energy service systems, an increasing number of automakers are exploring new solutions.

After the warranty period of an electric vehicle's power batteries expires, users of non-battery-swapping models must bear the potentially high costs of battery maintenance and replacement themselves. NIO's solution to this issue is the battery rental exchange mode, which utilizes the vehicle-to-battery separation technology and digital twin technology based on integration to offer a Battery-as-a-Service (BaaS) rental service. This service provides users with more flexible energy replenishment options while enabling intensive management of battery assets. The "Vehicle-to-Battery Separation" model constructed by BaaS has demonstrated unique advantages in the field of new energy vehicles, achieving systematic battery resource savings of at least 17% to 30% through optimized battery management and resource allocation. This model provides an economically efficient solution for users. Specifically, it manifests in two aspects:

- (1) By implementing a balanced battery swapping strategy, this model effectively integrates short-range battery packs with high-range ones. This approach achieves "average mileage" for batteries and prevents the premature retirement of high-range batteries. It ensures that batteries operate optimally at all times and enhances the overall energy efficiency of the BaaS system through optimized resource allocation.

- (2) Through centralized management of battery assets, more precise monitoring of battery health conditions is achieved. Real-time tracking of battery performance and status enables timely identification of potential issues, facilitating appropriate maintenance or replacement measures. This proactive maintenance strategy not only helps extend battery lifespan but also significantly reduces user operational costs in the long term, thereby creating conditions conducive to remanufacturing.

Owing to the extensive cycle regulation enabled by NIO’s battery swapping model, its power batteries can maintain an 80% State of Health (SOH) even after 12 years of use, significantly exceeding the current industry average of 70% SOH after 8 years. Based on this, in March 2024, NIO further proposed a long-life battery with a target lifespan of 15 years, maintaining a health level of $\geq 85\%$, and ensuring mileage reliability. This development is of great significance for both the industry and users.

There are various systems and models for battery management, but in comparison, mature battery-swapping models offer significant advantages (see Fig. 1). The traditional approach of combining slow and fast charging (commonly used in non-swappable battery vehicles) has the benefit of mature battery manufacturing technology and better battery stability. However, charging requires considerable wait time, and as the battery ages, users face higher costs for maintenance or replacement. Additionally, some breakthrough technologies allow vehicles to undergo supercharging. For instance, some electric vehicle Original Equipment Manufacturers (OEMs) rely on extensive supercharger networks for fast charging. However, supercharging technology has a significant impact on battery lifespan and places high demands on national grid power (public infrastructure capacity), including safety and reliability concerns.

In contrast, NIO’s battery-swapping model, with its balanced battery replacement strategy, greatly reduces waiting time and lowers the initial cost of vehicle ownership. This model not only enhances battery maintainability and lifespan but also provides flexibility for future battery technology upgrades, allowing users to easily benefit from the rapid advancements in battery technology by simply changing the service

Battery Management Approach	Unique Advantages	Areas for Improvement
Slow charging + fast charging	Stable battery technology, high vehicle integration.	Lower charging efficiency, considerable waiting time, and higher costs for maintenance or replacement.
Superchargers or DC fast charging	Faster charging speed, extensive coverage.	Impact on battery lifespan and places high demands on national grid power.
Battery swapping + leasing	Fast swapping, extended battery lifespan, flexible cost, and swapping stations serve as energy storage facilities.	High infrastructure costs.

Fig. 1 Comparative analysis among typical battery management systems

package. Most importantly, swapping stations can serve as energy storage facilities, helping to balance the national grid by storing energy during off-peak hours. However, the high infrastructure costs associated with swapping stations remain a major challenge, making it necessary to expand the swapping network further to boost its competitiveness.

2.2 Power Battery Remanufacturing

Another significant advantage of the battery swapping system is its facilitation of battery maintenance and remanufacturing. Once the vehicle and battery are decoupled, issues related to battery retirement or end-of-life ownership will no longer be contentious. The standardization and regulation of batteries enable unified disassembly methods. This facilitates the establishment of specialized robotic disassembly systems for retired batteries from battery-swapping vehicles. Consequently, it minimizes disassembly and recycling costs while maximizing the recovery rate of raw materials.

Based on extensive investigation and research at the NIO automotive factory, we identified the following issues in the current disassembly of SPBs:

- (1) The variety of batteries, with different models and sizes, poses difficulties for automated disassembly. Customization of production lines incurs high costs and results in low flexibility.
- (2) Efficient and safe disassembly of batteries at the end of their lifecycle is challenging with existing technologies, which struggle to form an industrialized disassembly model, necessitating the development of an efficient and feasible system.
- (3) The highly dynamic and complex tasks involved in robotic disassembly processes are prone to problems, requiring a comprehensive monitoring and interactive system to ensure efficient operations.

We have proposed targeted solutions to address these issues, with specific details to be elaborated in the next chapter.

3 Key Technology and System Design of Autonomous Disassembly Robot for Remanufacturing

3.1 *Intelligent Disassembly Technology for Robots Based on Neuro-Symbolic Artificial Intelligence*

In our previous work, we successfully implemented a NeuroSymbolic based robotic autonomous disassembly Task and Motion Planning (TAMP) system in a laboratory environment [20]. This system utilizes Planning Domain Definition Language (PDDL) [21] to define action primitives and employs neural predicates to convert multimodal information collected by the robot's multiple sensors into symbolic state representations in real time. An efficient state-space planner then generates a sequence of action primitives from the current state to the target state [22]. Each action primitive, such as moving, aligning, and inserting, is a minimal, indivisible action derived from the manual disassembly process and is defined in a knowledge-driven PDDL format. Each neural predicate is a neural network that processes multi-sensor inputs to determine the current state, such as whether the sleeve is aligned with the bolt or whether the sleeve is engaged with the bolt.

Furthermore, to address the search explosion in symbolic space primitive planning, we introduced large language models such as ChatGPT to achieve an efficient heuristic for task planning by using in-context learning and self-designed architecture [23]. Additionally, to accommodate more motion planning scenarios, we equipped the robotic arm with a movable chassis, forming a comprehensive Autonomous Mobile Manipulator Robot (AMMR), named BEAM-1 [24]. BEAM supports 12 different disassembly action primitives and 20 different types of sleeves. The “data and knowledge” dual-driven NeuroSymbolic system enables it to autonomously perform bolt disassembly tasks in large-scale, diverse, and highly dynamic environments.

3.2 *Cloud-Edge-Client System Design*

NeuroSymbolic AI enables the BEAM system at the laboratory stage to autonomously observe the environment, assess states and tasks, and decide on sequences of action primitives to execute, thereby autonomously completing wide-range bolt disassembly tasks. Furthermore, we are considering the efficient deployment of this entire technological approach in industrial settings to establish an industrialized closed-loop disassembly model, addressing the second challenge. We propose a CEC system (see Fig. 2).

We define the cloud computing layer as consisting of both public and private clouds. Public cloud services, which include large language models, will support task planning. Meanwhile, the private cloud, with its substantial computing power,

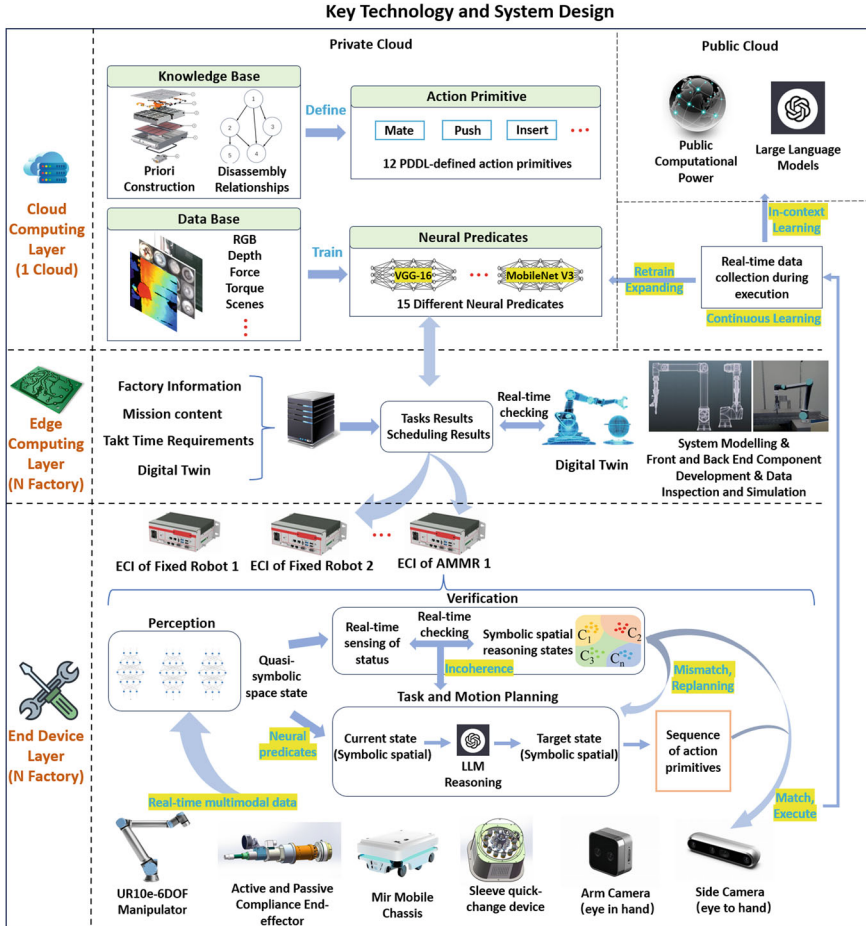


Fig. 2 Overview of key technical details and general architecture of the robotic autonomous disassembly system. Neurosymbolic AI-based autonomous disassembly industrialization model deployed by CEC System, equipped with digital twin

will handle action primitives driven by prior knowledge, such as battery structures and disassembly relationship diagrams. It will also manage neural predicates that require large data-driven training.

Resources and information from the cloud computing layer can be accessed by multiple edge computing layers. Here, we consider an edge computing layer to represent a factory with an independent computing center. Each factory has a flexible mixed-flow disassembly line [20] to accomplish various disassembly tasks. Within the edge computing layer, the system is responsible for formulating the task execution plan based on factory-specific information, takt time requirements, and digital twin computation results. Subsequently, this plan is communicated to the end devices,

Intel ECI. Additionally, the digital twin system of each factory should be deployed in the edge computing layer to ensure real-time monitoring and simulation.

Each Intel ECI in the edge computing layer serves as the central controller for either a fixed robot or an AMMR. Using BEAM as an example, the mobile chassis information, camera RGBD information, and actuator force/torque information are first perceived by neural predicates to determine the current state. Subsequently, the planner or large language model performs TAMP to generate the optimal sequence of action primitives from the current state to the target state. Validation and verification are conducted simultaneously. After each action primitive in the planned sequence is executed, we optimistically assume that the state in the symbolic space has changed as expected. This is then compared with the execution result perceived by the neural predicates. If discrepancies are found, re-planning is initiated.

The data for continuous learning is sourced from the execution process of action primitives. After each execution, since the neural predicates perceive the environmental state and compare it with the ideal state planned in the symbolic space, we can easily ascertain the outcome of each action primitive. Additionally, when a particular scenario is encountered multiple times, the neural predicates should memorize it. This allows for the use of more efficient and rapid action primitives for disassembly tasks when the same scenario arises again, akin to self-taught pre-programming. All this information will be uploaded to the cloud for training to optimize the accuracy and quality of the neural predicates and action primitives.

It is noteworthy that this deployment model is feasible because the edge computing layer does not require substantial computational resources. By utilizing an Intel ECI CPU combined with Neural Processing Units (NPUs), efficient real-time inference is achieved, significantly reducing costs. Continuous learning and network training occur in the cloud computing layer, which not only facilitates the centralized utilization of GPU computational resources but also allows for the extensive sharing of neural predicates and action primitives.

3.3 Digital Twin for Power Battery Disassembly Line

To address the challenges of remote control and interaction applications, we successfully deployed an autonomous disassembly workstation digital twin system at the edge computing layer (see Fig. 3). This system integrates physical and informational data, not only reflecting the real-time operational status of both the physical disassembly system and the virtual disassembly system but also enabling their real-time interactive control. The system construction primarily involves three key stages: constructing virtual scenarios, seamless integration with the real world, and intuitive human-machine interaction design.

The core objective of the virtual scene component is to construct high-precision twin models. We proposed a refined modeling technique to perform topological optimization on numerous invalid faces and unreasonable mesh distributions in the

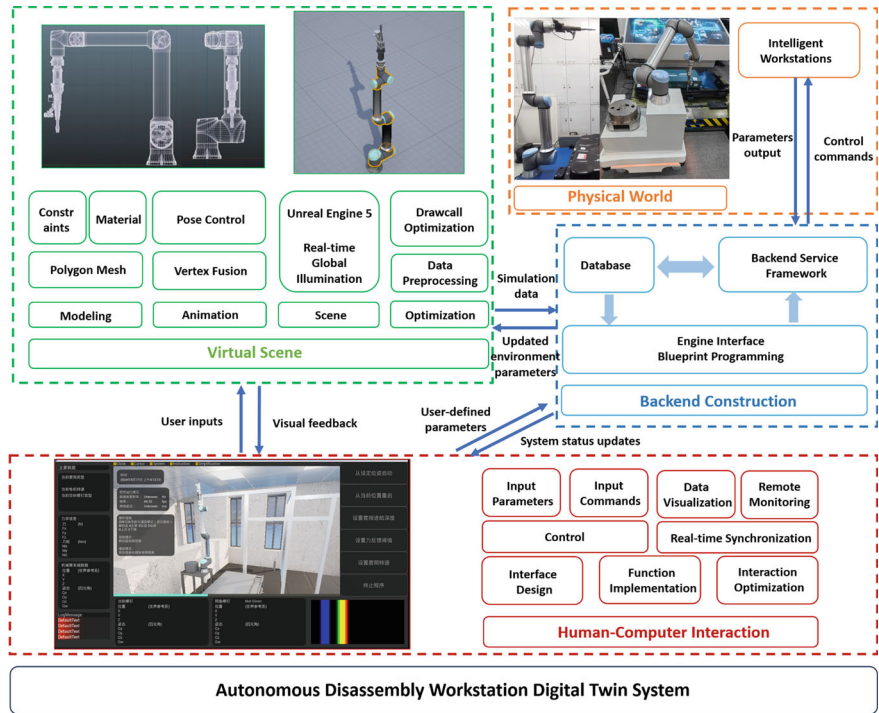


Fig. 3 Implementation of the Digital Twin System. The digital twin is deployed in the edge computing layer of each factory for monitoring, controlling, and simulating real-world scenarios

original model, establish model hierarchies and motion constraints, and finally render the models.

For human-machine interaction, we designed and implemented the human-machine interface for the digital twin system using the Unreal Engine (UE) platform [25, 26], achieving multi-source data integration and presentation. This includes the real-time display of posture, robotic arm movements, and sensor parameters, as well as real-time feedback for control interactions.

Addressing the maturity challenges of current digital twin technology in remote control applications, we propose employing the Python Django [27] framework as the backend service architecture for the digital twin system. Utilizing SSH communication technology, we deploy Python Django backend programs to the factory's on-site workstation servers and employ an intranet mapping strategy to map the backend service port addresses to a public domain name. The Unreal Engine frontend communicates remotely with the backend by sending HTTP requests to the public domain name. This setup, combined with MySQL cloud databases [28] for dynamic data storage, facilitates efficient interaction and control between clients and workstation servers, significantly enhancing the practicality of the digital twin system.

4 Conclusions

4.1 *Contribution of Remanufacturing-Oriented Autonomous Disassembly Robots to the Remanufacturing Industry*

This paper takes NIO as an example to analyze its energy service system and discuss the necessity of SPBs remanufacturing. In response to the practical issues encountered during the disassembly process, we designed a NeuroSymbolic based autonomous disassembly robot for SPBs, deployed using the CEC architecture, and developed a corresponding digital twin system. NeuroSymbolic AI enables our system to autonomously perform disassembly in highly dynamic environments, with diverse disassembly objects and complex disassembly processes, without any pre-programming. This not only reduces labor costs and mitigates disassembly risks but also contributes to the sustainable development of the remanufacturing industry. This technological architecture supports a circular economy and also aligns with global efforts to achieve sustainable development goals.

4.2 *Perspective*

To promote the vigorous development of the battery remanufacturing industry, it is imperative to establish a responsibility-sharing mechanism involving industry stakeholders, government agencies, and consumers. Industry participants can focus on design for remanufacturing and invest in remanufacturing facilities. The government can encourage remanufacturing practices through policies, subsidies, and regulatory frameworks. Consumers can drive demand by participating in recycling programs and choosing remanufactured products.

The future of battery remanufacturing is closely linked to the formulation of comprehensive policies and regulations. These policies should address standardized procedures for battery collection, transportation, and storage, as well as safety and environmental standards for the remanufacturing process. Additionally, reasonable quantitative standards should be established to diagnose whether a battery's health necessitates remanufacturing.

In the field of robotic disassembly, we will continue to dedicate efforts to the research of autonomous disassembly technology for power batteries by using NeuroSymbolic AI, striving to enhance the efficiency and cost-effectiveness of remanufacturing operations. This fundamentally transforms the battery remanufacturing and disassembly industries, making them more flexible, efficient, and sustainable.

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