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From Data to Decisions: Leveraging Large Language Models and Digital Product Passports for Data-Driven Remanufacturing

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Abstract

Remanufacturing plays a key role in advancing the circular economy by extending product lifecycles and reducing resource consumption. However, its effectiveness is often constrained by incomplete lifecycle data and high uncertainty in the returned products. Digital Product Passports (DPPs) enhance transparency and traceability, but their heterogeneous, unstructured, and dynamically evolving data within them limits the effectiveness of obtaining actionable insights for remanufacturing. Generative AI (GenAI), particularly large language models (LLMs) offer new capabilities for interpreting heterogeneous data, maintaining long-term context across circular production, including collection, disassembly, remanufacturing, testing, and redistribution. This paper explores the convergence of DPP, GenAI, and remanufacturing, evaluating their synergies and integration challenges. We propose a generative agent-based model where LLMs interact dynamically with DPPs to support real-time quality assessment, operational planning, instruction generation, and interactive diagnostics. Finally, we identify key research directions and technical challenges for building interoperable, GenAI-enhanced platforms that realize data-driven, DPP-enabled remanufacturing.

Keywords: Remanufacturing; Digital Product Passport; Large Language Models; Circular Economy

1. Introduction

Amid growing concerns over raw material scarcity and the pursuit of long-term sustainability goals, the circular economy (CE) has emerged as a critical pillar for guiding the industry toward a more resource-efficient future [1]. CE strategies, which aim to extend product lifecycles through material recovery and reuse, may generate up to $4.5 trillion in economic benefits by 2030 [2, 3]. Within this paradigm, remanufacturing has proven to be one of the most promising approaches for closing the loop on industrial production [4].

A prominent example of CE implementation is the rapid global adoption of electric vehicles (EVs), with projections estimating that over 145 million EVs will be on the road by 2030. However, this growth is accompanied by the challenge of managing an estimated 12 million tons of end-of-life lithium-ion batteries [5]. Remanufacturing plays a critical role in restoring these batteries to like-new condition, a process that demands highly customized and adaptive operations [6, 7]. Traditionally, such operations have relied heavily on manual inspections and functional testing conducted by experienced human operators. These conventional methods are labor-intensive, time-consuming, and costly, ultimately constraining both the scalability and reliability of remanufacturing systems [8–10].

DPPs are emerging as promising tools to enhance transparency, traceability to customize remanufacturing workflows [11]. By consolidating technical specifications, product metadata, maintenance logs, and performance metrics for each battery, DPPs support condition assessment, part tracking, and regulatory compliance. For battery regulation, DPPs may include manufacturer information, design specifications, materials, and composition [12, 13]. When augmented with real-time sensor inputs and test results, including impedance measurements, di-

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agnostic images, or functional test results, these data sources form a comprehensive, context-rich profile for each battery unit [14]. However, the inherent heterogeneity and unstructured nature of DPP-related data still pose significant challenges for both human operators and conventional AI or statistical methods to interpret efficiently [9, 15].

Recent advances in LLMs offer new opportunities to interpret and integrate complex data environments. LLMs have demonstrated potential in identifying patterns from diverse inputs, generating contextual summaries, and engaging with users through natural language [16, 17]. In technical domains, LLMs can reason across structured and unstructured data sources, such as engineering documentation, sensor streams, and historical logs [18], while producing task-specific outputs that assist human decision-making [19, 20].

However, LLMs are limited by the context window length and lack domain-specific knowledge, which leads to the risk of hallucination. To address these challenges, this paper proposes a generative agent-based model to distribute the decision authority to different LLM agents, who collaboratively identify the optimal plan. Each LLM agent is supported by a domain-specific LLM responsible for processing relevant DPP data, interpreting sensor inputs, incorporating prior agents' outputs, and responding to operator prompts. By incorporating human-in-the-loop review, the proposed method offers informed decision support while ensuring all decisions are generated under human guidance throughout the EV battery remanufacturing process. The main contributions of this work are:

1. Proposed a generative agent-based model that addresses the limitations of LLMs' context windows while integrating domain-specific knowledge.
2. Repurposed LLM to process heterogeneous remanufacturing data, including DPP subsets, sensor streams, prior agent outputs, and human-in-the-loop prompts, to generate product-specific decision support.
3. Demonstrated the synergistic potential of LLMs and DPPs through a case study simulating EV battery remanufacturing under diverse conditions.
4. Developed a human-centric approach by preserving human oversight and decision-making in remanufacturing.

The paper is structured as follows: Section 2 reviews recent literature. Section 3 presents our generative agent-based model and formal task structure. Section 4 describes the case study setup and implementation. Section 5 presents results from selected stages of the remanufacturing workflow. Section 6 summarizes key findings and outlines directions for future work.

2. Related Work

Remanufacturing decision-making involves numerous interdependent factors, such as part condition, labor cost, quality variability, and process flexibility that impact economic and operational success [21, 22]. However, making these decisions effectively is often hindered by fragmented data, uncertainty around returned product condition, and a lack of scalable decision-support tools [23].

Emerging technologies such as DPPs and LLMs offer promising pathways to improve transparency, integrate lifecycle context, and enable adaptive process control in remanufacturing. DPPs, in particular, are gaining traction as a regulatory and technological cornerstone of the EU's sustainability strategy [24–26], offering traceability through standardized encoding of product metadata. Gleich et al. proposed a DPP architecture based on Asset Administration Shells to facilitate interoperable information exchange and carbon footprint tracking [27]. Psarommatis and May outlined the benefits of DPPs in remanufacturing, focusing on reducing required work time and proposing structured integration methods [28].

In the context of lithium-ion batteries, Thunyaluck and Valilai demonstrated how DPPs can support vertical and horizontal data integration across supply chain levels [11]. Meanwhile, LLMs are being integrated into industrial systems to enhance reasoning and automation capabilities [29]. Specifically for remanufacturing, Ji et al. applied LLM-assisted reinforcement learning to optimize task allocation in hybrid disassembly lines, showing measurable improvements in efficiency and ergonomics [30]. However, the combined use of LLMs and DPPs in remanufacturing remains underexplored. Existing studies tend to focus on either structured data pipelines or the automation potential of LLMs in isolation. Our research closes that gap by proposing an integrated LLM–DPP framework that translates data into customized decision support for each used product.

3. Methodology

3.1. Generative Multi-Agent Model for Remanufacturing

To address the challenges, we propose a generative agent-based model, composed of T LLM agents:

$$A = \{A_t\}_1^T,$$

where each agent A_t is responsible for a specific remanufacturing stage, for example, $t \in \{\text{assess}, \text{disass}, \text{insp}, \text{reass}, \text{test}\}$, corresponding respectively to assessment, disassembly, inspection, reassembly, and testing. At each stage t, the LLM agent receives the inputs: (i) a relevant subset of the DPP data $\mathbf{d}_t$, (ii) selected outputs from the prior agent, (iii) supplemental sensor data $\mathbf{s}_t$, and (iv) the task-specific prompts h_t authored by human operator. The agent then produces outputs intended to support and align with operator decision-making at that stage.

The first stage, A_{assess}, generates an initial condition assessment of the returned product. A_{disass} then uses these assessments to construct a condition-aware disassembly plan. Next, A_{insp} evaluates parts and classifies their reuse potential. A_{reass} synthesizes the reassembly plan, and A_{test} recommends validation tests and generates standardized logging templates. The interactions and information flows between agents are illustrated in Figure 1. To enhance reliability and reduce hallucination, each agent is restricted to domain-specific inputs, and all outputs are subject to human review to identify omissions or inaccuracies and guide regeneration.

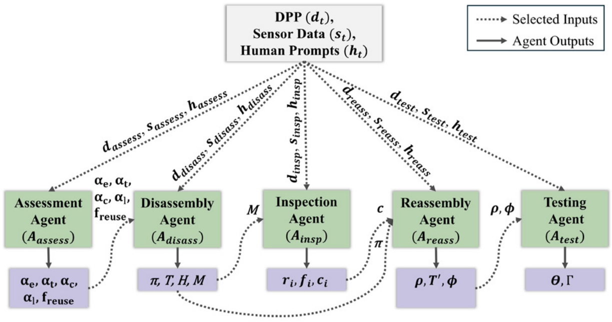

Fig. 1. Information flow among agents in the remanufacturing process.

3.2. Assessment Agent ($\boldsymbol{A}_{assess}$)

The assessment agent evaluates the product's reusability based on the provided DPP $\mathbf{d}_{\text{assess}}$, sensor data $\mathbf{s}_{\text{assess}}$, and human operator prompt h_{assess}. Specifically:

$$A_{\text{assess}}: \left(\mathbf{d}_{\text{assess}}, \mathbf{s}_{\text{assess}}, h_{\text{assess}}\right) \rightarrow \left(\alpha_e, \alpha_t, \alpha_c, \alpha_z, f_{\text{reuse}}\right), \quad (1)$$

Prompt: `"Assess external, terminal, casing, and label conditions."`

The inputs are provided as follows: $\mathbf{d}_{\text{assess}} = [\texttt{id}, \texttt{mfg\_date}, \texttt{SoH}, IR, L]$ encodes product metadata including identifier, manufacturing date, state-of-health (SoH), internal resistance (IR), and maintenance history. $\mathbf{s}_{\text{assess}}$ contains the image of the returned product, and h_{assess} is a task-specific human operator prompt.

For outputs, $\alpha_e, \alpha_t, \alpha_c, \alpha_z$ are textual condition assessments corresponding to the product's external condition, terminal condition, casing integrity, and traceability, respectively. These assessments are explained in short phrases (e.g., "obscured and likely corroded"). $f_{\text{reuse}} \in \{\texttt{bad}, \texttt{poor}, \texttt{fair}, \texttt{good}, \texttt{excellent}\}$ denotes the reuse eligibility category for the agent to classify.

3.3. Disassembly Agent ($\boldsymbol{A}_{disass}$)

The disassembly agent executes only if $f_{\text{reuse}} \neq \texttt{bad}$; otherwise, the product is routed to recycling. When triggered, the agent returns the condition-aware outputs:

$$A_{\text{dis}}: \left(\mathbf{d}_{\text{disass}}, \boldsymbol{\alpha}, \mathbf{s}_{\text{disass}}, h_{\text{disass}}\right) \rightarrow \left(\boldsymbol{\pi}, \mathcal{T}, \mathcal{H}, \mathcal{M}\right), \quad (2)$$

Prompt: `"Disassembly plan with safety, recommended tools, and annotated parts."`

The inputs $\mathbf{d}_{\text{disass}} = [\texttt{chem}, S, T_{\max}, \texttt{prod\_type}]$ include the product's chemistry, specifications, safe handling temperature range, and type. The inclusion of $T_{\max}$ enables A_{disass} agent to incorporate thermal safety constraints when generating disassembly instructions, selecting appropriate tools, and providing operator guidance. $\boldsymbol{\alpha} = [\alpha_e, \alpha_t, \alpha_c, \alpha_z]$ are the condition assessments from the prior A_{assess} outputs. $\mathbf{s}_{\text{disass}}$ includes internal images. h_{dis} is the human operator prompt at this stage.

The outputs are: $\boldsymbol{\pi} = [\pi_1, \ldots, \pi_K]$, the recommended disassembly plan; $\mathcal{T}$, recommended tool list; $\mathcal{H}$, safety guidance for human operators; $\mathcal{M} = \{m_i\}$, annotated disassembled parts including ID, name, quantity, and contextual explanation (e.g., reason for removal or their influences in the disassembly plan).

3.4. Inspection Agent ($\boldsymbol{A}_{insp}$)

The inspection agent estimates the RUL and reusability of each part based on the provided four inputs:

$$A_{\text{insp}}: \left(\mathbf{d}_{\text{insp}}, \mathcal{M}, \mathbf{s}_{\text{insp}}, h_{\text{insp}}\right) \rightarrow \{(r_i, f_i, c_i)\}_{i=1}^{N}, \quad (3)$$

Prompt: `"Estimate RUL, assess part reuse, and summarize part annotation."`

Here, $\mathbf{d}_{\text{insp}} = [E, V, C, L]$ includes the part's data: expected lifetime, nominal voltage, capacity, and maintenance history. $\mathcal{M}$ refers to the annotated list of disassembled parts generated by A_{disass}. $\mathbf{s}_{\text{insp}}$ includes test results such as impedance and thermal readings, as well as image data. h_{insp} represents the operator prompt specific to this stage.

For each part i, A_{insp} returns the triplet (r_i, f_i, c_i), where $r_i \in [0, 100]$ is the estimated RUL expressed as a percentage of the part's original expected lifetime under normal operating conditions, $f_i \in \{\texttt{reuse}, \texttt{replace}, \texttt{discard}\}$ indicates the reusability classification based on functional and visual assessments, and c_i provides part-level annotations including ID, quantity, and condition tags (e.g., cosmetic wear, insulation damage).

The classification f_i is determined according to the following rule-of-thumb heuristic, which is predefined by human preference: parts with $r_i \geq 75\%$, no critical defects, and successful test results are classified as reuse. Parts with r_i between 30% and 74%, or showing minor degradation, are marked as replace. Components with $r_i < 30\%$ or those failing critical safety or functionality tests are recommended for discarding.

3.5. Reassembly Agent ($\boldsymbol{A}_{reasm}$)

The reassembly agent generates the adaptive reassembly plan and updates parts annotation accordingly:

$$A_{\text{reasm}}: \left(\mathbf{d}_{\text{reasm}}, \{\boldsymbol{\pi}, \boldsymbol{c}\}, \mathbf{s}_{\text{reasm}}, h_{\text{reasm}}\right) \rightarrow \left(\boldsymbol{\rho}, \mathcal{T}', \Phi\right), \quad (4)$$

Prompt: `"Generate reassembly plan, suggest required tools, and update parts annotation."`

The input $\mathbf{d}_{\text{reasm}} = [S, L]$ captures the part specifications and maintenance history. The set $\{\boldsymbol{\pi}, \boldsymbol{c}\}$ reflects the selected outputs from A_{dis} regarding disassembly plan and parts annotation from A_{insp}. $\mathbf{s}_{\text{reasm}}$ contains part substitution logs. h_{reasm} provides operator guidance and domain inputs. The outputs include $\boldsymbol{\rho} = [\rho_1, \ldots, \rho_\theta]$, the reassembly plan with precautions; $\mathcal{T}'$, recommended tools for reassembly; $\Phi = \{\phi_i\}$, reannotated parts with updated condition and reassembly notes.

3.6. Testing Agent ($\boldsymbol{A}_{test}$)

The testing agent is designed to generate the test plan and logging format to verify the final remanufactured product:

$$A_{\text{test}}: \left(\mathbf{d}_{\text{test}}, \boldsymbol{\rho}, \Phi, \mathbf{s}_{\text{test}}, h_{\text{test}}\right) \rightarrow \left(\boldsymbol{\theta}, \Gamma\right), \quad (5)$$

Prompt: `"Suggest validation tests and measurement templates."`

The vector $\mathbf{d}_{\text{test}} = [S, n]$ includes specifications and expected performance limits. The reassembly plan $\boldsymbol{\rho}$ and parts annotations Φ are from outputs of A_{reass}. $\mathbf{s}_{\text{test}}$ captures relevant sensor logs (e.g., voltage curves, thermal signatures). h_{test} is prompt from the human operator. Here, the outputs contain $\boldsymbol{\theta} = [\theta_1, \ldots, \theta_p]$, a set of test steps for the test plan, and Γ, the corresponding test data logging schema.

3.7. DPP Extension and Feedback Integration

Following the completion of the remanufacturing workflow, a final step is performed to update the product's DPP. Rather than incorporating all intermediate outputs, only those results that are both relevant and verified by the human expert are selectively appended to the original DPP record.

$$\mathcal{U}_{\text{DPP}}: \ (\mathbf{d}_0, \mathcal{D}, \Delta Z) \rightarrow \mathbf{d}_{\text{final}}. \tag{6}$$

Prompt: `"Select prior disassembly steps output and consolidate into the DPP format."`

Here, $\mathbf{d}_0$ denotes the complete initial DPP available at the start of the remanufacturing process, containing product metadata such as identifier, specifications, and historical service records. After all agents have executed, the set $\mathcal{D}$ includes selected agent outputs, such as part-level condition annotations (c), reuse decisions (f), procedural steps ($\boldsymbol{\pi}, \boldsymbol{\rho}$), and test results ($\boldsymbol{\theta}, \Gamma$) that have been reviewed and approved for archival. The term ΔZ captures any additional expert-authored corrections or annotations not directly produced by the generative agents. The extension operator $\mathcal{U}_{\text{DPP}}$ integrates the selected outputs and expert revisions with the initial passport $\mathbf{d}_0$, resulting in an enriched DPP $\mathbf{d}_{\text{final}}$ to close the loop of LLM-DPP interactions.

4. Case Study

To evaluate the proposed generative agent-based model, we conducted a case study on the 2019 Audi A3 Sportback e-tron hybrid battery pack, demonstrating how agents support decision-making across key stages of EV battery remanufacturing. Three DPP datasets were synthesized for representative battery packs, labeled α, β, and γ. Data in the DPP, such as voltage range (280–390 V), nominal energy (8.8 kWh), and configuration (8 modules, 96 cells) were referenced from [31, 32], while additional condition categories' value (e.g., SoH ranges, IR trends) and maintenance log assumptions were synthesized by the authors to simulate diverse product conditions.

Each battery DPP data captured key attributes, including nominal energy capacity, voltage range, expected lifetime, operating temperature limits, SoH, IR, and material composition. To evaluate the agent's performance, we adopted a reference procedure derived from prior literature [31]. This baseline includes twelve disassembly steps (i–xii), along with mappings of main components (1–17) and associated fasteners (A–I), covering structural disassembly, electronic component removal, cooling system extraction, and complete module separation. Leveraging the synthesized DPPs, relevant sensor data, and human prompts, we instantiated all stages of the EV battery remanufacturing process. Each stage was executed by an LLM agent powered by GPT-4o, with domain-specific context and knowledge constructed through prompt engineering. In Section 5, we present selected outputs from each stage, demonstrating how the agents contributed to the decision support under varying product conditions.

5. Results

5.1. Initial Assessment

In the initial stage, A_{assess} analyzed relevant information from the DPP and supplemental sensor inputs to assess each battery's condition. Guided by human prompts, A_{assess} evaluated physical and electrical indicators, including SoH, IR, historical maintenance records, and external condition imagery, shown as a summary to inform the human's subsequent decisions.

Criterion	Battery α	Battery β	Battery γ
State of Health (SOH)	58% (Low)	76% (Moderate)	85% (High)
External Condition	Aged and dirty; signs of environmental wear	Moderate wear; mild surface corrosion	Clean and well-preserved
Terminal Condition	Obscured and likely corroded	Partially visible, light dirt	Appears clean; terminals likely intact
Casing Integrity	Structurally intact, minor corrosion	Solid with cosmetic wear	Excellent condition, no defects
Traceability	Label intact; QR and serial number visible	Label clear and scannable	Label in excellent condition; fully traceable
Reusability	Poor; heavy degradation and leakage history	Fair; minor degradation, reworkable	Excellent; minimal degradation, reusable as-is
IR Trend	Many modules >25% IR increase	One module +18% IR	All modules nominal
Warning Flags	Multiple modules degraded; leak in 2024	One module slightly degraded; minor leak in 2023	None
Maintenance History	2021, 2023, 2024 (leak)	2021, 2023 (minor leak)	2022

Fig. 2. Condition assessments generated by the agent for batteries α, β, and γ.

As shown in Figure 2, A_{assess} evaluated the three battery packs. Battery α was rated poor in reusability due to severe degradation, including corroded terminals, a 2024 leakage event, and rising IR. Battery β showed moderate wear, with minor corrosion and localized IR elevation, supporting a fair reuse decision pending further inspection. Battery γ maintained high integrity across all indicators, with clean terminals and stable IR, and was classified as an excellent classification for reuse.

5.2. Disassembly

The disassembly stage (Figure 3), Battery α, previously classified in poor condition, was assigned full disassembly by A_{disass}. Battery β, with moderate degradation and limited internal risk, was recommended a truncated plan: steps i–vii were executed, with partial completion of cooling and module access (viii–x). Full module extraction (xii) was unnecessary; only modules flagged by IR anomalies were inspected or replaced.

Battery γ, showing excellent assessment, required minimal disassembly. A_{disass} limited operations to safety checks, casing removal, and traceability verification (i–v), with partial sampling of two modules (ix–x). All other steps, particularly electronic and cooling system removals (vi–viii, xi), were skipped.

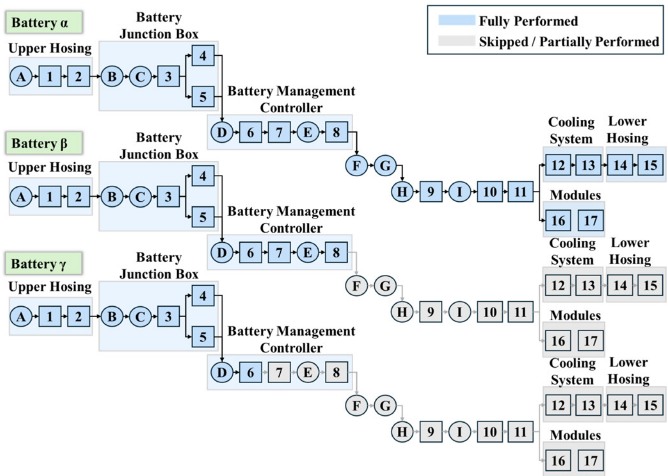

Fig. 3. Comparison of disassembly plans generated for three batteries, with reference to the baseline procedure from [31].

5.3. Part-Level Inspection and Reusability Evaluation

The disassembled components were evaluated by A_{insp}, which integrated part metadata, functional test results, and sensor inputs to estimate RUL and classify reusability. Figure 4 presents part of the inspection results for Battery α. The components exhibited a wide range of degradation: non-critical parts, such as the housing shell, were classified as reusable after cosmetic cleaning, whereas several electrical components were deemed unsuitable due to performance loss or insulation wear. The high-voltage cable and connector assemblies, although functionally continuous, were recommended for replacement because of damaged insulation and reduced RUL.

Ref.	Name	Qty.	Condition Tags	RUL Est.	Reusability Decision
1	Upper housing shell	1	Scratched, dusty surface	80% (cosmetic)	Reuse after cleaning
2	Upper insulator	1	Clean	95% (functional)	Reuse
3	Plug-in cable between BJB and CMCs–BMC	1	Worn insulation, passed continuity test	60% (functional)	Replace
4	Battery Junction Box (BJB)	1	Terminal discoloration	65% (functional)	Replace
5	High Voltage cables and connectors	1	Cracked insulation, passed continuity test	50% (functional)	Replace
6	Top transverse covers	2	Surface scratched	90% (cosmetic)	Reuse
7	Plug-in cable CMCs–BMC	1	Anchors cut; cable intact	90% (functional)	Reuse after re-anchoring

Fig. 4. Example of inspection agent output for battery α.

5.4. Reassembly

Reassembly plans, shown in Figure 5, were generated by A_{reass} based on validated part annotations, sensor inputs, and the prior disassembly plan. For Battery α, which underwent a full teardown, the agent recommended a complete nineteen-step reassembly process, including system reintegration and validation. For Battery β, the agent suggested a selective plan in which only accessed subsystems, primarily modules and controllers, were restored, while unmodified components (e.g., BMS, cooling plate) were left intact to reduce handling. For Battery γ, which required only minor inspection-related removals, the agent proposed a minimal sequence focused on reinstalling two sampled modules, reconnecting controllers, and restoring covers and cabling.

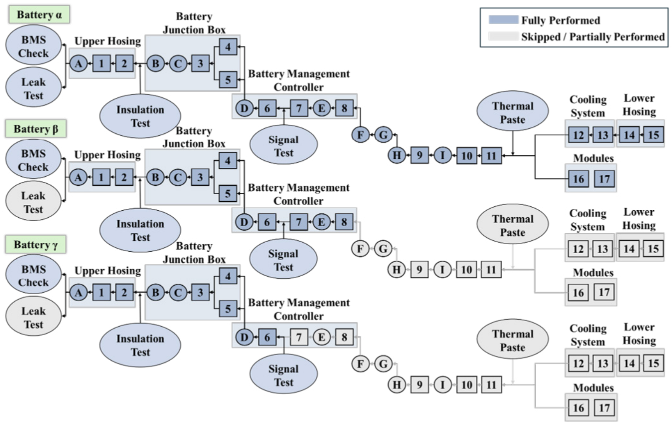

Fig. 5. Comparison of disassembly steps performed across batteries.

6. Conclusion

This study presented a generative multi-agent model that integrates LLMs with DPPs to support product remanufacturing. The model distributes tasks across five stages: assessment, disassembly, inspection, reassembly, and testing, so that each agent operates on relevant DPP data, sensor inputs, and operator prompts. By repurposing LLMs to process heterogeneous remanufacturing data, the model can generate actionable decision support to assist technicians in carrying out safe, efficient, and product-specific operations.

The case study on EV battery remanufacturing demonstrated how the model can assess product condition, adapt disassembly depth, evaluate part reusability, and generate reassembly plans under varying conditions. Although batteries were used as the demonstration case, the proposed generative agent-based model is applicable to other remanufactured products, provided that comprehensive passport data are available. Initiatives such as the EU's DPP and the U.S. Cyber-Physical Passport (CPP) are expected to further enhance feasibility.

Future work will incorporate quantitative evaluation, including disassembly time, accuracy of RUL estimates, and efficiency of DPP updates. In addition, metrics such as the Metric for Evaluation of Translation with Explicit Ordering (METEOR) will be applied to assess how well agent-generated instructions and annotations align with human-authored references. Additionally, we plan to pilot the generative agent-based model in a smart factory environment to validate its effectiveness in real-world remanufacturing workflows and gather feedback from domain experts for iterative refinement.

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References

[1] H.-H. Hsieh, K.-C. Yao, C.-H. Wang, C.-H. Chen, S.-H. Huang, Using a circular economy and supply chain as a framework for remanufactured products in the rubber recycling industry, Sustainability 16 (7) (2024). doi:10.3390/su16072824.

[2] J. Korhonen, A. Honkasalo, J. Seppälä, Circular economy: the concept and its limitations, Ecological economics 143 (2018) 37–46.

[3] U. Dayal, M. Gupta, D. Ghosh, D. Wadhawan, A. Morrow, S. Horiguchi, H. Wang, A. Rao, A. Osling, C. Gupta, et al., Enabling product circularity through big data analytics and digitalization, in: 2022 IEEE 65th International Midwest Symposium on Circuits and Systems (MWSCAS), IEEE, 2022, pp. 1–6.

[4] Y. H. Kim, W. Ye, R. Kumar, F. Bail, J. Dvorak, Y. Tan, M. C. May, Q. Chang, R. Athinarayanan, G. Lanza, et al., Unlocking the potential of remanufacturing through machine learning and data-driven models—a survey, Algorithms 17 (12) (2024) 1–26.

[5] A. A. Adejare, R. K. Tagayi, J. Kim, Enhancing power substation reliability with second-life battery energy storage systems for dynamic fault mitigation in grid-scale applications, Electric Power Systems Research 241 (2025) 111372.

[6] D. Klohs, C. Offermanns, H. Heimes, A. Kampker, Automated battery disassembly—examination of the product-and process-related challenges for automotive traction batteries, Recycling 8 (6) (2023) 89.

[7] G. Harper, R. Sommerville, E. Kendrick, L. Driscoll, P. Slater, R. Stolkin, A. Walton, P. Christensen, O. Heidrich, S. Lambert, et al., Recycling lithium-ion batteries from electric vehicles, nature 575 (7781) (2019) 75–86.

[8] Battery Pass Consortium, Battery passport value assessment, https://thebatterypass.eu/assets/images/value-assessment/pdf/2024_BatteryPassport_Value_Assessment.pdf, accessed: 2025-07-08 (2024).

[9] J.-P. Kaiser, S. Lang, M. Wurster, G. Lanza, A concept for autonomous quality control for core inspection in remanufacturing, Procedia CIRP 105 (2022) 374–379.

[10] T. Lachnit, A. Deckert, M. Hörger, K. Gleich, F. Bail, M. Benfer, G. Lanza, Modelling and analysis of circular production network structures, in: Decarbonizing Value Chains, Springer Nature Switzerland, Cham, 2025, pp. 725–733.

[11] M. Thunyaluck, O. F. Valilai, Integrating digital product passports in multi-level supply chain for enabling horizontal and vertical integration in the circular economy, in: 2024 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 2024, pp. 36–42.

[12] A. Pohlmann, M. Popowicz, J.-P. Schöggl, R. J. Baumgartner, Digital product passports for electric vehicle batteries: Stakeholder requirements for sustainability and circularity, Cleaner Production Letters 8 (2025) 100090.

[13] Battery Pass Consortium, Battery passport content guidance (version 1.0, july 2023), https://thebatterypass.eu/assets/images/content-guidance/pdf/2023_Battery_Passport_Content_Guidance.pdf, pDF report (2023).

[14] O. Ondemir, S. M. Gupta, Quality assurance in remanufacturing with sensor embedded products, in: Quality Management in Reverse Logistics: A Broad Look on Quality Issues and Their Interaction with Closed-Loop Supply Chains, Springer, 2012, pp. 95–112.

[15] C. Lopes, J. Barata, Digital product passport: A review and research agenda, Procedia Computer Science 246 (2024) 981–990.

[16] J. P. Inala, C. Wang, S. Drucker, G. Ramos, V. Dibia, N. Riche, D. Brown, D. Marshall, J. Gao, Data analysis in the era of generative ai, arXiv preprint arXiv:2409.18475 (2024).

[17] P. Bouquet, A. Molinari, S. Sandri, Challenges in working with unstructured data in the llm era: Ner processes using graph neural networks, in: 2024 4th International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), IEEE, 2024, pp. 1–6.

[18] X. Li, A. Nassehi, H. Yang, F. Tao, J. Sutherland, L. Wang, R. Gao, Generative manufacturing systems, SSRN preprint http://dx.doi.org/10.2139/ssrn.5405092 (2025).

[19] Z. Keskin, D. Joosten, N. Klasen, M. Huber, C. Liu, B. Drescher, R. H. Schmitt, Llm-enhanced human-machine interaction for adaptive decision making in dynamic manufacturing process environments, IEEE access (2025).

[20] X. Li, A. Nassehi, S. J. Hu, B. G. Joung, R. X. Gao, A large manufacturing decision model for human-centric decision-making, CIRP Annals (2025).

[21] J. Dvorak, L. Stanzl, T. Lachnit, M. Benfer, F. Balzereit, G. Lanza, On the systematic selection of ce strategies for end-of-life-products: A guide for practitioners, in: K. Dröder, T. Vietor (Eds.), Circularity Days 2024, Springer Fachmedien Wiesbaden, Wiesbaden, 2025, pp. 229–242.

[22] T. Lachnit, I. Vetter, C. Braun, T. von Glasenapp, J. Feng, M. Benfer, G. Lanza, Comprehensive assessment of remanufacturing suitability and enhancement, in: Decarbonizing Value Chains, Springer Nature Switzerland, Cham, 2025, pp. 572–579.

[23] M. I. Rizova, T. Wong, W. Ijomah, A systematic review of decision-making in remanufacturing, Computers & Industrial Engineering 147 (2020) 106681.

[24] E. Commission, A new circular economy action plan for a cleaner and more competitive europe, European Commission: Brussels, Belgium (2020) 1–20.

[25] European Commission, Proposal for a Regulation of the European Parliament and of the Council establishing a framework for setting ecodesign requirements for sustainable products and repealing Directive 2009/125/EC (COM(2022)142 final), https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52022PC0142, document COM(2022)142 final; procedural reference 2022/0095(COD) (Mar. 2022).

[26] European Parliament and Council of the European Union, Regulation (EU) 2023/1542 of the European Parliament and of the Council of 12 July 2023 concerning batteries and waste batteries, amending Directive 2008/98/EC and Regulation (EU) 2019/1020 and repealing Directive 2006/66/EC, https://eur-lex.europa.eu/eli/reg/2023/1542/oj/eng, official Journal L191, 28July2023, pp.1–117 (Jul. 2023).

[27] K. Gleich, S. Behrendt, M. Hörger, M. Benfer, G. Lanza, An asset administration shell-based digital product passport as a gaia-x service, Procedia CIRP 127 (2024) 224–229.

[28] F. Psarommatis, G. May, Digital product passport: a pathway to circularity and sustainability in modern manufacturing, Sustainability 16 (1) (2024) 396.

[29] M. Raza, Z. Jahangir, M. Riaz, et al., Industrial applications of large language models, Scientific Reports 15 (2025) 13755.

[30] P. Ji, X. W. Guo, J. Wang, W. Wang, S. J. Qin, Y. Tang, Q. Kang, Reinforcement learning with large language model for hybrid disassembly lines in remanufacturing contexts, in: 2024 IEEE 20th International Conference on Automation Science and Engineering (CASE), 2024, pp. 1981–1986.

[31] M. Alfaro-Algaba, F. J. Ramirez, Techno-economic and environmental disassembly planning of lithium-ion electric vehicle battery packs for remanufacturing, Resources, Conservation and Recycling 154 (2020) 104461.

[32] Audi UK, Audi a3 sportback e-tron – full uk specification, https://press.audi.co.uk/assets/documents/original/11271-AudiUK00000441A3SportbacketronFullUK.pdf, accessed: 2025-07-08 (2024).

[33] S. Khan, A. Haleem, N. Fatma, Effective adoption of remanufacturing practices: a step towards circular economy, Journal of Remanufacturing 12 (2) (2022) 167–185.