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A sustainable echelon re-utilization and recycling for dynamic end-of-life electric vehicle battery packs

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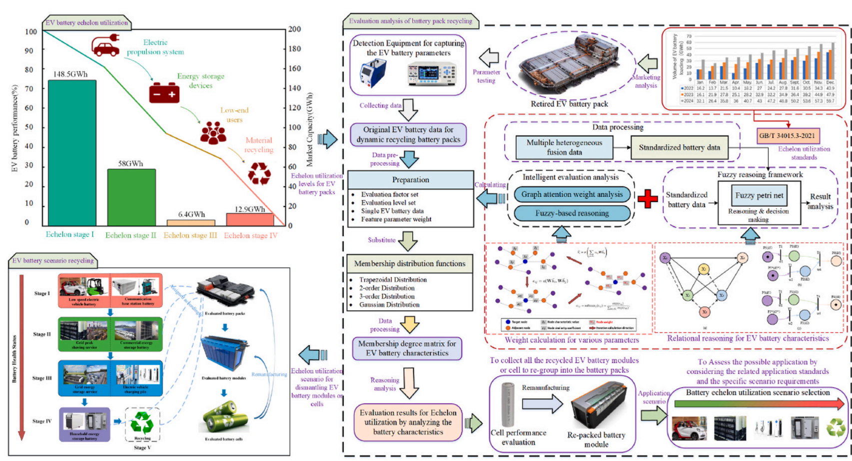
HIGHLIGHTS

- The dynamic strategies of EV battery pack recycling are recommended by the application scenarios of echelon utilizations.
- Graph attention mechanism determines the parameter analysis of EV battery pack evaluations.
- Rule-based reasoning model obtains different evaluation results with performance parameters.
- The EOL battery characteristics involve the relational mining based on the standard of GB/T_34015.3–2021.

GRAPHICAL ABSTRACT



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ABSTRACT

Electric vehicle (EV) batteries inevitably degradation with long-term use that hierarchically reuse EV battery packs after meeting their related recycling standards to maximize its potential values by application environments, battery characteristics, product types, etc. However, these factor uncertainties pose a major challenge to effective evaluation from inconsistent performance, widely varied remaining capacities, and potential safety concerns. Therefore, it is imperative to achieve a more accurate evaluation for echelon re-utilization to provide a sounder rationale for decisions regarding the recycling of EV battery modules or cells. In this paper, a reasonable and efficient intelligent evaluation system has been provided to solve these challenges caused by the uncertainties of EV battery packs that hierarchically consider the possible applications of echelon re-utilization and recycling. The unique contribution of this system lies in its novel integration of knowledge reasoning with relation mining, which surpasses traditional evaluation methodologies by systematically analyzing the complex and intrinsic dependencies among various battery characteristics, moving beyond simple parameter-based assessments. Moreover, big data calculation and relation analysis of EV battery pack characteristics with GB/T_34015.3–2021 standard can be used to recommend the possible scenarios of echelon re-utilization and

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recycling. Finally, a case study was conducted using 18650 lithium iron phosphate (LFP), Nickel-Cobalt-Manganese (NCM), and Nickel-Cobalt-Aluminum (NCA) batteries to validate the proposed methodology by evaluating the echelon re-utilization and the selection of application scenarios based on complex data analysis and relation mining.

1. Introduction

With the ongoing degradation of climate and environment, continuous energy consumption has become a growing concern for Electrical Vehicle (EV) battery recycling. However, U.S. has begun to advocate the echelon re-utilization of EV battery packs, which can be repurposed for various applications such as standalone power supply, wind energy integration, and residential energy storage. EU countries have also placed greater emphasis on the EV battery recycling, involving many companies (e.g., Bosch in Germany, BMW Group, etc.) to develop large-scale echelon re-use solutions for EV battery disposals. China is also actively advancing policies related to carbon peaking and neutralization, which drive the sustainable development of green, low-carbon transformation and green economy, especially for EV product recycling (Yin et al., 2023). As one of the world's largest energy consumers, China is promoting the development of EV technology, alongside the restructuring of its industrial sector and the electrification of its power system (Xiao et al., 2023). According to national statistics, the number of EV in China had reached 31.4 million by the end of 2024. In the same year, a total of 12.86 million new energy vehicles were sold in the country. The recycling volume of EV batteries in China has reached 654, 000 tons in 2024 corresponding to the first batch of EV batteries (Guan et al., 2025). Currently, EV battery recycling may not have reached their full potential through multiple echelon application scenarios so that it is essential to reuse EV battery packs for the sustainable development of circular economy.

As shown in Fig. 1, the EV battery loading volume demonstrates a sustained growth trend from 2022 to 2024, which is closely related to the expanding market demand and the active promotion of national industrial policies (Guo et al., 2024). However, the rapid growth of new energy vehicle market has made efficient EV battery recycling a significant challenge, posing a barrier to further development. Compared to high-emission fuel vehicles, EV battery cars have too many benefits with minimal pollution, lower driving noise, relatively simple structure, and easier maintenance (Xiao et al., 2022). New energy vehicles, however, inevitably come with certain drawbacks, such as higher power costs and shorter driving ranges compared to gasoline-powered vehicles. As the battery's maximum capacity gradually deteriorates due to its chemical characteristics, it experiences permanent capacity loss, eventually falling below the threshold to support vehicle performance (Butylskii et al., 2024). The recycling of EV battery packs will be a potential research direction, enabling the echelon re-utilization of EV battery in different application scenarios, such as large-scale energy storage, household energy, etc. (H. Chen et al., 2022).

With the continued development of waste battery market, it is necessary to establish the systematic evaluation and prediction of waste EV battery within the recycling sector. To enhance energy utilization efficiency in large-scale EV battery recycling, the research into the secondary use of waste EV batteries has become increasingly valuable, aiming to optimize battery performance throughout its entire lifecycle (Xiao et al., 2021). The waste EV battery can be repurposed as a medium or small-scale energy storage solutions for applications such as household energy storage, which can be separated into the modules or cells to reuse them with respects to their performance and potential values. This process, known as echelon re-utilization, enables the classification of EV battery packs into various application scenarios, including grid-connected energy storage systems, residential energy storage devices, mobile electric storage devices, and personal charging devices. However, the direct recycling of EV battery packs would result in the significant waste of resource and the contamination of environment. Therefore, it is essential to implement echelon re-utilization to evaluate their economic feasibility and extend their lifespan before the directed disposals (Gao et al., 2025). Currently, the echelon re-utilization of EV battery packs from various business applications lacks standardized guidelines, making it difficult to effectively assess the possible echelon applications into downstream industrial production and commercial reuses. Moreover, since EV battery packs are produced by different manufacturers without a unified production standard, their structural diversity presents a major challenge. In addition, the uncertain operational histories and environmental conditions of EV battery packs result in significant variations in the characteristics of each retired EV battery. The current echelon utilization evaluation methods, however, often oversimplify the reality by typically assessing battery parameters as isolated, independent values, under the assumption that no intrinsic connections or dependencies exist between them. The parameters are intrinsically linked, and it is the complex dependencies (e.g. the dynamic interplay between internal resistance, capacity, and state of health) that makes an accurate evaluation for echelon re-utilization exceedingly complex (Zhang et al., 2025). As a result, several research questions must be addressed to analyze this uncertainty and to unlock the potential commercial value of retired EV battery pack recycling.

- There is currently no standardized approach to evaluate the hierarchical applications of EV battery packs according to its specific

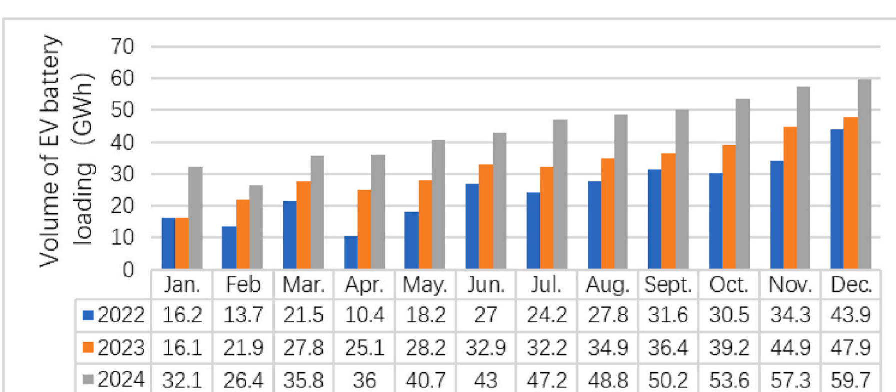

Fig. 1. The volume of monthly EV battery loading (GWh) from 2022 to 2024.

health status and possible application scenarios. Therefore, it is essential to develop an efficient and intelligent evaluation analysis for the possible echelon utilization applications.

- Due to the inherent performance uncertainty of retired EV battery packs during the echelon reutilization and recycling, it is difficult to find out an optimal echelon evaluation approach for retired EV battery packs with uncertainty. Clearly, it is essential to explore the relationship between the characteristic parameters in the retired EV battery echelon recycling.

In response to the research questions associated with retired EV battery recycling, the paper proposes a novel dynamic echelon analysis method for battery characteristics and the intricate dependencies among them by integrating graph attention mechanism with comprehensive data and relation evaluations. The objective is to effectively address the discrepancies between battery characteristics caused by the inherent uncertainty of EV batteries. This is achieved through a 'dynamic' approach, which involves a targeted evaluation of each battery state and a tailored analysis of its echelon utilization scenarios based on its unique characteristics. Ultimately, the effectiveness of this evaluation method is validated and demonstrated using multiple datasets from actual 18650 lithium iron phosphate (LFP), Nickel-Cobalt-Manganese (NCM), and Nickel-Cobalt-Aluminum (NCA) batteries. The rest of this paper is organized as follows. Section 2 outlines the key challenges of echelon re-utilization and explores the application scenarios to optimize specific recycling strategies. Section 3 details the proposed methodology combining graph attention mechanism with complex data and relation evaluation to analyze the possible echelon scenarios. Section 4 demonstrates the application of evaluation analysis model through sample testing based on various characteristics of EV battery packs. Section 5 and Section 6 discusses the potential research directions and conclusions.

2. Literature review

Grounded in the EU waste hierarchy (Rossi et al., 2015) and the Ellen MacArthur Foundation's circular economy framework (Provin et al., 2024), end-of-life strategies are prioritized by retaining products and materials at their highest functional value before material recovery. In this study, we adopt the following working definitions tailored to EV batteries. Reuse (second-use) refers to using a pack or module again with the same function after basic safety and performance checks. Repurpose denotes second-life use with a different function, for example converting traction applications to stationary storage, potentially with reconfiguration. Refurbish/remanufacture refers to restoring performance to acceptable standards through repair or component replacement. Recycling denotes the recovery of materials, such as metals, at end-of-life.

Against this backdrop, the optimal recycling of retired EV battery packs is gradually maturing, with increasing focus on the feasibility of echelon re-utilization. Lih et al. (2012) proposed a recovery approach for EV batteries based on a practical project from an economic perspective, demonstrating significant economic value in energy storage applications. The retired EV battery packs are typically categorized into four gradient levels for echelon re-utilization based on their remaining capacity and characteristics: electric propulsion system, energy storage device, low-end user, material recycling. As shown in Fig. 2, the growing demand for retired EV battery packs highlights the substantial market potentials at each stage, with estimated market capacities observed in 2024 (Yang et al., 2024).

2.1. EV battery pack echelon utilization

The echelon re-utilization of EV battery packs has been extensively studied by many scholars as shown in Table 1. A review of the literature reveals that numerous scholars have explored various aspects of EV battery echelon re-utilization. Neubauer et al. (Neubauer and Pesaran, 2011) proposed an economic model to evaluate the feasibility of reusing EV batteries in the re-manufacturing process. Deshpande et al. (2012) developed an EV battery aging mechanism model to accurately forecast battery lifespan across a wide temperature range based on mechanical stress and chemical deterioration. Gorrachategu et al. (Sanz-Gorrachategui et al., 2021) proposed a battery life modeling approach to anticipate the EV batteries life for grid peak shaving applications. The accurate prediction of battery performance and other key parameters is crucial for assessing the potential of EV batteries for echelon reuse. Li et al. (Li and Cao, 2017) proposed an efficient prediction model that incorporates temperature, charge status, and discharge depth to forecast EV battery capacity, revealing the impact of temperature on battery degradation. Podias et al. (2018) examined battery capacity attenuation that found it to be a non-linear process to progress steadily over time. Rajaeifar et al. (2022) proposed a prediction model to evaluate the EV batteries to recommend their recycling strategies. These studies collectively highlight the importance of evaluating the potential for echelon re-utilization of EV batteries using optimization techniques and predictive evaluation methods by comparing various recycling index of retried EV battery packs.

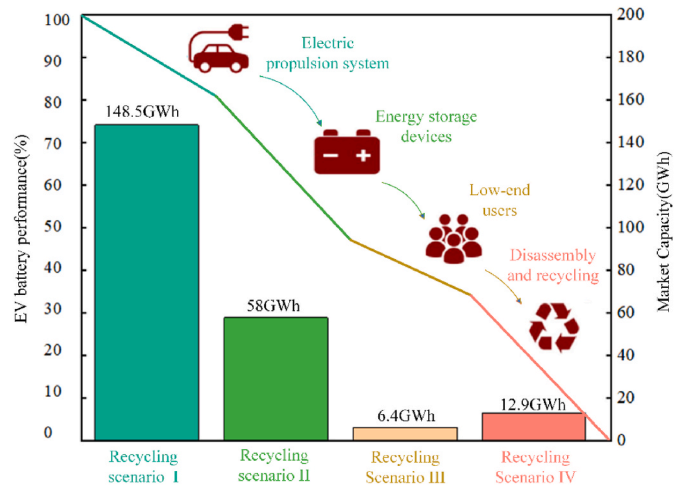

Fig. 2. The general market demands of retired battery packs through echelon re-utilization and recycling.

Despite its potentials, the echelon utilization of EV battery packs faces several challenges that hinder the efficiency of recycling processes. According to Song et al. (2019), excessively high costs associated with wind energy integration and battery renewal significantly limit the feasibility of reuse applications. Simultaneously, numerous academic studies have explored the possible battery recycling roadmaps from various perspectives and developed the assessment or prediction models, which contribute to more effective and efficient optimization of echelon utilization scenarios. Madlener et al. (Madlener and Kirmas, 2017) proposed an economic model to explore the economic feasibility of secondary-use batteries for electric vehicles in various application scenarios. Similarly, the evaluation methods for retired EV batteries can assess the economic benefit for their real echelon applications, Jiao et al. (Jiao and Evans, 2016) proposed a cluster analysis method to screen the EV batteries based on the key characteristics and parameters, which provided the possibility of improving the performance of EV battery echelon utilization. Narang et al. (2024) investigated the impact of carbon trading prices, reward-penalty intensity, company-related costs, and competition coefficients on retired power batteries by using actual market data and Stackelberg game theory, aiming to select the most suitable recycling model for the batteries. Zhao et al. (2018) developed an evaluation method for EV batteries to drastically reduce working hours, which successfully screened EV batteries to predict the capacity of retired EV battery packs. The optimal echelon utilization of EV

Table 1
The related works of echelon utilization for EV battery recycling.

Contents of echelon utilization for EV battery recycling	Ref.	Economic benefit & costs	Aging mechanism	Lifecycle forecasting	Parameter characteristics
Recycling process optimization	Wu et al. (Wu et al., 2022)	✓			✓
	Reis et al. (Reis and Jiang, 2022)			✓	✓
	Han et al. (Han et al., 2018)	✓		✓	
	Chen et al. (Chen et al., 2020)		✓	✓	
	Ghosh et al. (Ghosh et al., 2021)				✓
Application scenario decision-makings	Baumann et al. (Baumann et al., 2018)	✓			✓
	Oda et al. (Oda et al., 2022)		✓		
	Rohr et al. (Rohr et al., 2017)			✓	
	Zhao et al. (Zhao et al., 2022)	✓		✓	
	Lai et al. (Lai et al., 2021a)	✓		✓	✓

batteries can be achieved by evaluating key characteristics such as battery residual capacity, internal resistance, low-temperature discharge capacity, charge discharge temperature increase, and high magnification discharge capacity. To effectively assess their feasibility of possible echelon application scenarios, it is essential to acquire the optimal influencing factors for these parameters. These data can guide the selection of appropriate evaluation analysis in accordance with recycling procedures and relevant industry standards tailored to the characteristics of EV batteries.

2.2. Echelon utilization evaluations

Typical evaluation methods for echelon utilization include Analytic Hierarchy Process (AHP), Projection Pursuit Evaluation (PPE), Entropy Weight (EW) and Fuzzy Comprehensive Evaluation (FCE). The AHP method is designed to handle multi-level decision-making by assigning the weights of different performance factors, effectively capturing the complexity of the problem. However, it is often criticized for its high degree of subjectivity and reliance on a heavily hierarchical structure, which may not be ideal for evaluating complex and uncertain performances of retired EV batteries (Kumar and Pant, 2023). The PPE method can be used to transform high-dimensional data into low-dimensional representations for visualization and analysis, which has high requirements for data before data pre-processing. Based on the characteristics of the original data, EW method adaptively determines the weight of each factor by measuring the degree of variation, thereby minimizing the influence of correlations among multiple factors (Dubois and Prade, 2015). The FCE method can handle the fuzziness and uncertainty between multiple evaluation indexes, which makes the result more comprehensive and accurate by incorporating membership degrees and rule and logic variables (X. Chen et al., 2022). Li et al. (2011) proposed the entropy weight method by simple and convenient analysis for the practical recycling application. Bai et al. (Bai and Asgarpoor, 2004) proposed a comprehensive evaluation method to determine the possibility distribution of characteristic factors by analyzing its feasibility. Lin et al. (2007) discussed a comprehensive evaluation method to demonstrate the possible evaluation model. Kaya et al. (2019) proposed a multi-objective decision-making method to address energy decision-making problems and achieve effective data processing. Chen et al. (2015) discussed the uncertainties inherent in rule-based evaluation methods, enhancing the accuracy of complex evaluations.

The parameters of retired EV battery packs play a crucial role in determining the evaluation levels of EV battery echelon utilization, which needs to have a quantified parameter for the final evaluation result before the evaluation analysis. Due to the uncertainty of EV battery structures and their quality, it is necessary to develop standardized parameters for echelon analysis methods. Furthermore, quantifying the evaluation parameters of EV battery parameters is challenging when assessing the battery echelon utilization due to the high complexity and uncertainty. Traditional evaluation methods are known to exhibit a certain subjective tendency for complex evaluation analysis, as they often rely heavily on expert knowledge to pre-define rules or assign fixed weights to various parameters. This reliance not only introduces subjectivity but also struggles to capture the full spectrum of complex, non-linear interactions inherent in battery systems. To overcome this limitation, a paradigm that can objectively and automatically learn these intricate relationships directly from data is required. Graph Neural Networks (GNNs), operating on graph-structured data, have emerged as a powerful framework to address this specific challenge. The rationale behind using a graph-based methodology lies in its fundamental mechanism to mitigate subjectivity, which represents battery characteristics as nodes and models their potential interdependencies as edges in a graph. Crucially, instead of relying on manual pre-sets, a GNN automatically learns and quantifies the importance of these edges through end-to-end training based on the data. This data-driven process effectively replaces the subjective, experience-based process of expert weighting. By doing so, the graph mechanism fundamentally reduces the reliance on a priori expert knowledge and subjective judgment, offering a more objective and precise solution for complex evaluation analysis. Graph attention network (GAT) incorporates an attention mechanism to quantify the correlation between node data with the evaluation parameters, thereby effectively capturing the complex relationships among various parameters (Veličković et al., 2018). The proposed method offers a novel perspective and solution for quantifying the related parameters of EV battery. Graph attention mechanism has more advantages over traditional entropy weight and hierarchical analysis for the evaluation methods. Graph attention mechanism can automatically learn the relationship between various nodes through the graph-structured data without manually setting parameters, thereby reducing the subjectivity to improve the efficiency of evaluation analysis. Similarly, graph attention mechanism can capture more complex relationships through information transfer between various nodes, while traditional methods may not perform well when handling complex evaluation scenarios.

As shown in Table 2, a comparative analysis between graph attention mechanism and traditional evaluation methods is presented to highlight their respective advantages across various characteristics, including method complexity, processing requirements, compatibility, relationship analysis, and reasonability. Although graph attention mechanism may involve greater complexity in model construction compared to traditional methods, this complexity offers increased flexibility and adaptability in handling diverse and dynamic evaluation scenarios. The graph attention mechanism has high requirements for data processing relying on high-quality graph structure and node data. It employs a data-driven approach to parameter allocation and decision-making, which reduces the interference of subjective judgment to improve the rationality and reliability of the evaluation results. Compared with traditional methods, the graph attention mechanism not only provides more objective evaluation results but also, more importantly, captures the mutual influence among battery parameters. This dual advantage leads to more efficient and reliable decision-making. In conclusion, combining the graph attention mechanism with comprehensive evaluation methods

Table 2
The comparisons of various characteristics and parameter calculations.

Evaluation analysis methods	Computing complexity	Data processing requirements	Compatibility with various models	Internal relationship analysis	Result reasonability
Entropy weight method(Li et al., 2022)	Low	No	Strong	No	Weakness
Graph attention mechanism(Moradi et al., 2025)	High	Yes	Strong	Yes	Strong
Analytic Hierarchy Process(Sáenz-Royo and Chiclana, 2025)	Low	Yes	Strong	Yes	Weakness
Fuzzy comprehensive evaluation with rules(Sheng et al., 2025)	High	Yes	Weakness	Yes	Strong
Knowledge reasoning evaluations with rules(Liu et al., 2025)	Higher	Yes	Strong	Yes	Stronger

is essential for effectively assessing the application scenarios of EV battery echelon recycling. Based on the reviewed research, it is essential to implement the echelon utilization of EV batteries to achieve energy conservation and environmental protection. Due to the uncertainty and variability of retired EV battery characteristics, there is currently no standardized evaluation system tailored to the specific EV battery characteristics, which greatly affects the efficiency and results of the evaluations. This paper proposes a highly efficient evaluation method that incorporates multi-parameter characteristics, combining the graph attention mechanism and comprehensive data and relation evaluation to enhance the feasibility and viability of the evaluation system.

3. Knowledge reasoning and relation evaluation method

As known, it is essential to propose an evaluation model based on graph attention mechanism and comprehensive data and relation evaluation method to determine the analytical way to the possible echelon utilization scenario for retired EV batteries (Li et al., 2009). Furthermore, the evaluation of characteristic factors and their respective parameters can be determined by considering a data set for each indicator. Using the relationship matrix and the membership function, the data set of each index is derived based on the contribution of each index for the evaluation objects. Through the comprehensive knowledge reasoning algorithm, all indices can be synthetically considered to acquire the optimal evaluation results (Xu et al., 2023). In traditional evaluation analysis, the parameters distribution of evaluation indicators often relies on the subjective expert knowledge, which might lead to the bias and inconsistency in the evaluation results. Specifically, there are complex intrinsic connections and mutual influences between the status parameters of EV battery recycling, such as battery capacity decay, battery cycle life, and battery residual value. However, traditional methods fail to capture the dynamic relationship between these parameters limiting the accuracy and reliability of the evaluation results. To overcome this limitation, Graph Attention Networks (GATs) offer a novel solution by constructing a knowledge graph that connects the various feature factor relationships based on the original data. In the graph structure, each node represents a feature factor, while the edges denote the interactions between these characteristic factors. The graph attention mechanism dynamically calculates the weight of each feature factor, reflecting both the individual parameter data of each factor and the mutual influences among them. The dynamic calculation refers to the ability of the proposed model to address the uncertainty and heterogeneity of EV batteries. Specifically, the graph attention mechanism captures the unique parametric characteristics of each battery, re-computing a tailored set of parameter weights each time it evaluates a new battery pack. The core advantage of GAT algorithm lies in its ability to reflect the complex relationship between feature factors of EV battery packs or modules. In contrast to traditional evaluation methods, it more accurately simulates the multi-dimensional influencing factors in the recycling of EV batteries, providing more detailed evaluation results. Additionally, GAT enhances the interpretability of graph structure to intuitively understand the different factors, thereby providing a more scientific evaluation analysis for retired EV battery recycling.

However, the characteristic parameters of EV batteries exhibit complex interdependencies. For instance, as the battery degrades, the increase in internal resistance directly influences the degree of temperature rise during its operation. Such intrinsic physical and logical relationships cannot be fully captured by the GAT's analysis at the level of battery parameter data alone. To enhance the reliability and accuracy of the evaluation, the results from the GAT are then subjected to rule-based reasoning through the Fuzzy Petri Net (FPN). The FPN operates as a complementary step, applying predefined rules based on domain knowledge and physical constraints to optimize and refine the evaluation outcomes. This step ensures that the evaluation is consistent with known theoretical and practical limits, providing a more robust and validated result. In summary, the GAT is not a standalone classifier but rather an essential tool for uncovering hidden relationships in the data, while the FPN ensures that these findings are validated and aligned with expert knowledge. Together, they form a comprehensive evaluation framework that balances data-driven learning with rule-based optimization.

Therefore, a characteristics evaluation analysis of retired EV batteries has been proposed by considering a GAT-based evaluation model as shown in Fig. 3. EV battery pack can be analyzed by the battery testing tools to obtain the original battery status parameters, which serve as key input data for the evaluation process. Once the data is collected, it can be further analyzed and verified through the relation reasoning process to ensure the feasibility of the GAT-based evaluation process. The relation reasoning process also helps to enhance the interpretability of the graph structure relationships, which is crucial for understanding the model decision-making that can be used to improve the accuracy of the evaluation results. Based on practical experience and existing literature, the characteristic factor set and evaluation set of retired EV battery historic data can be constructed to define the key factors as corresponding evaluation criteria within the evaluation process. By considering the graph attention-based evaluation methods, the data and relations of each characteristic factor in the echelon utilization performance evaluation can be calculated to reflect the significance of each factor in the evaluation of EV batteries and their mutual influences. Subsequently, the proposed model employs various relationships based on membership allocation functions to perform characteristics evaluation of retired EV battery packs or modules, which maps the battery status parameters to the evaluation set, thereby providing a quantitative description of the battery status. Finally, by analyzing the computing results, the model not only enables assessment of overall battery performance but also supports rational selection of different echelon re-utilization scenarios for retired EV batteries.

As shown in Fig. 4, it shows the procedure of the data calculation based on the GATs to determine the performance analysis of EV battery parameters for the echelon utilization scenario. Fig. 4 (a) constructs a knowledge graph that includes battery-related parameters and evaluation levels, highlighting the interrelationships between battery parameters in the context of the echelon utilization evaluation of retired EV battery packs or modules. The relationships marked with red lines

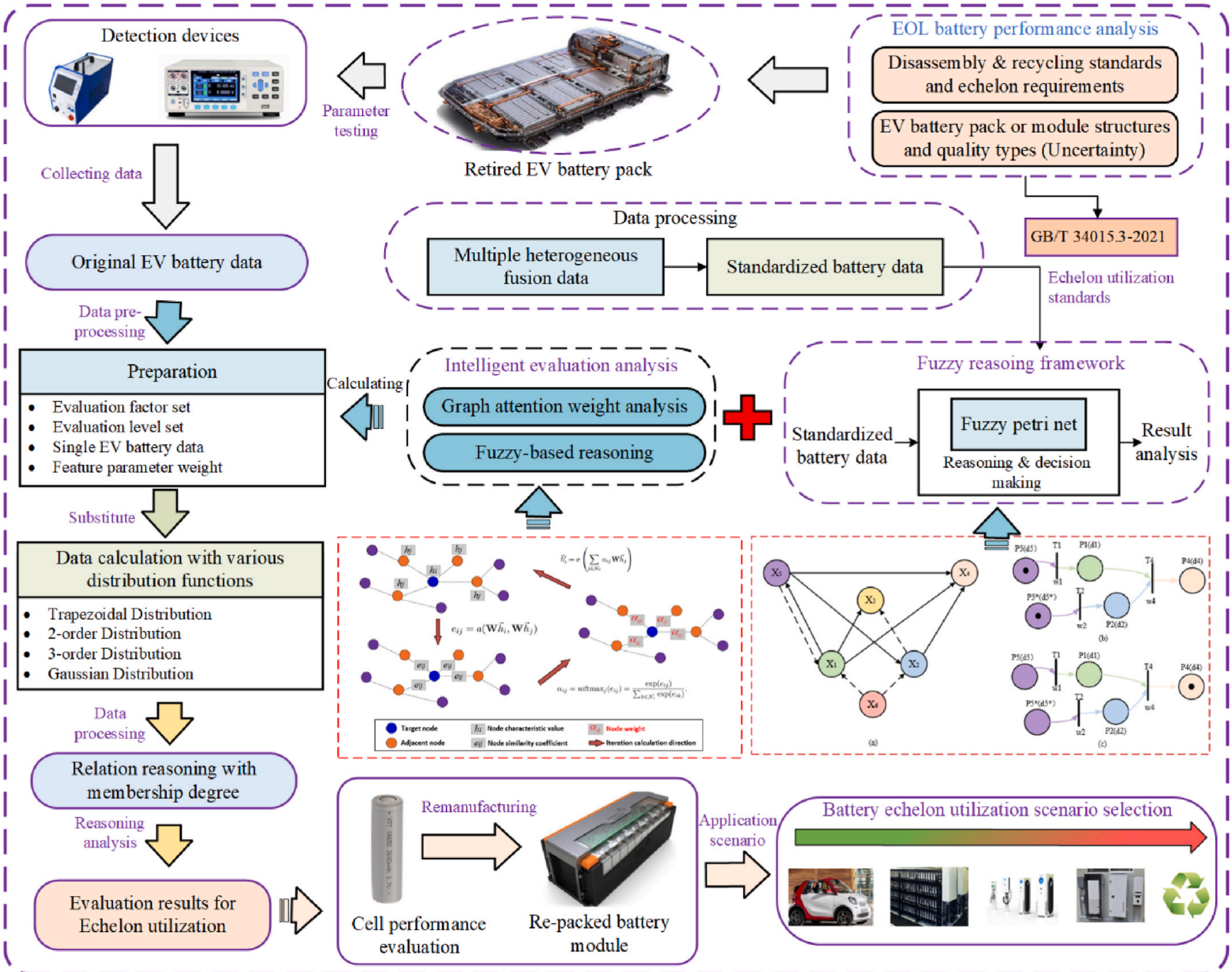

Fig. 3. Overview of the evaluation procedure combining knowledge reasoning and characteristics evaluation for EV battery packs or modules.

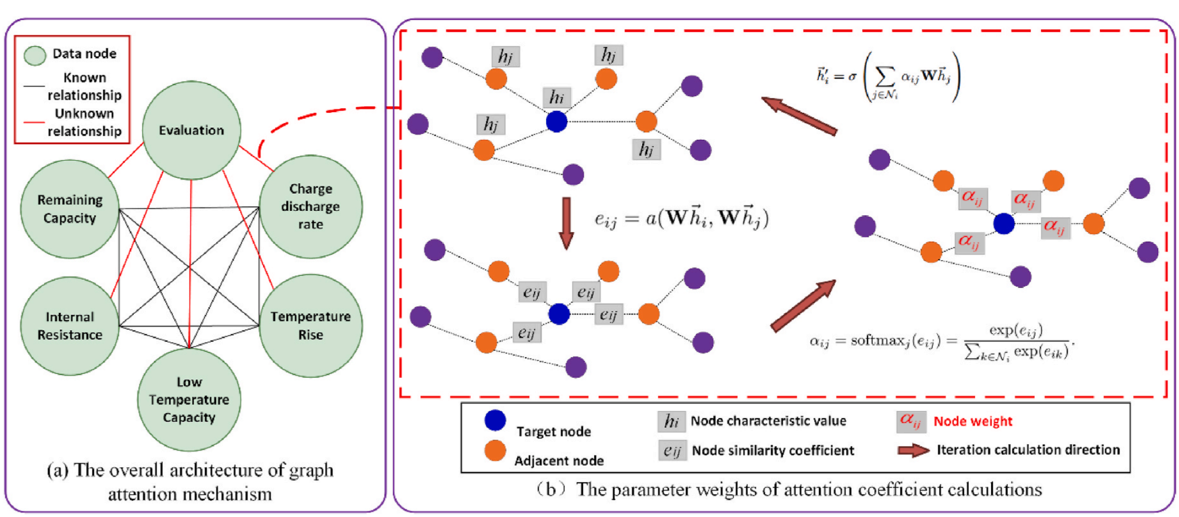

Fig. 4. The analysis of evaluation characteristics based on GAT-based knowledge data and relation reasoning.

represent the influencing factors of battery parameters for the evaluation results. The relationships are concretized and quantified numerically through the GAT-based process reasoning. Furthermore, Fig. 4 (b) describes the procedure of calculating the influencing factors between nodes by the graph-based process reasoning. Therefore, for any target node, the influencing factors of its adjacent nodes are calculated using the multiple attention mechanism. In the i-th iteration, it can be described as the feature of the target node h_i, the feature of its adjacent nodes h_j, and the similarity coefficients e_{ij} between the adjacent nodes and the target node.

$$e_{ij} = a\left(Wh_i \| Wh_j\right) \tag{1}$$

Where W is the weight matrix related to the node features of the input and output results. $\|$ represents the bonding of tensors; a is the training attention kernel related to the node that can be used to optimized through iterative training. After the similarity coefficients of all adjacent nodes and the target node can be obtained, the influencing weight α_{ij} can be calculated by normalizing them.

$$\alpha_{ij} = soft\max\left(e_{ij}\right) = \frac{exp\left(e_{ij}\right)}{\sum_{k \in N} exp\left(e_{ik}\right)} \tag{2}$$

The graph-based attention evaluation method will fully consider the intrinsic relationship between nodes through iterative learning to obtain the relatively accurate influencing factors. The obtained weights of adjacent nodes are aggregated to generate new features of the target node h_i'. The new target node features can be analyzed and compared with the original node features to further optimize the feature matrix W and attention kernel a of the next iteration. After multiple iterations, a relatively stable target influencing weight can be described as.

$$h_i' = \sigma\left(\sum_{j \in N} \alpha_{ij} W_{h_j}\right) \tag{3}$$

Based on the architecture, it is necessary to design the pseudocode implementation of the parameter training algorithm. By using the graph-based evaluation framework as shown in Fig. 4, the weight matrix W and attention coefficients α are initialized firstly. During the forward propagation phase, node feature can be represented to compute by using the GAT-based data and relation evaluation method, and the iteratively updated node features are compared with the ground truth data Y, which represent the actual characteristics of the EV batteries (e.g., their real-world performance data). These reference data serve as a benchmark to evaluate the model's performance, not as manually labeled data for supervised learning. Subsequently, in the backpropagation phase, the weight matrix W is optimized via gradient descent. The training process terminates when the error between the updated node features and the real-world data falls below a predefined convergence threshold, indicating model convergence. Finally, the weight matrix W for retired EV battery parameters is output as the result.

Algorithm 1. Graph attention network for EV battery parameter evaluation

Input: Battery parameter graph $H \in R^{n \times d}$, Adjacency matrix $A \in \{0,1\}^{(n \times n)}$, Ground truth $Y \in R^{n \times d}$, Learning rate η , Epochs T
Output: Trained weight matrix W, Attention parameters α
1: Initialize $W \in R^{d \times d'}$ with He normal//Feature transformation
2: Initialize $\alpha \in R^{2d'}$ with Xavier//Attention mechanism
3: $ELU \rightarrow \Theta$ activation parameters//Nonlinear function
4: for $t = 1$ to T do
5://———— Forward Propagation ————6: $H' = H \times W$//Linear transformation
7: Compute $E = \left[e_{ij}\right]$ via Eq. (1): $e_{ij} = a^T\left(Wh_i \| Wh_j\right)$
8: $\alpha =$ softmax(E)//Normalized attention (Eq. (2))
9: $h_i' = \sigma^*\left(\sum_{j \in N} \alpha_{ij} Wh_j\right) \rightarrow H^*$//Aggregation (Eq. (3))
10: $Y' = FC(H^*)$//Final prediction layer
11://———— Backward Propagation ————12: Compute $L = MSE(Y', Y)$//Loss

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(continued)

function
13: $\frac{\partial L}{\partial \theta} \rightarrow \nabla W, \nabla \alpha, \nabla \Theta$//Gradient computation
14: Update parameters with Adam:
$W - \eta \nabla W \rightarrow W$,
$\alpha - \eta \nabla \alpha \rightarrow \alpha$,
15: end for 16: return (W, α)//Trained model parameters

The GAT-based evaluation analysis has been thoroughly explained in accordance with the specific practical engineering requirements. Therefore, it is imperative to analyze the effective echelon utilization of retired EV batteries using a case study involving multiple battery packs with the GAT method. However, assessing the potential echelon recycling strategy is a dynamic process that relies on multi-source data collection and relation mining. The graph-based evaluation analysis relies on analyzing specific battery data sets to assess the state of EV battery echelon re-utilization and recycling. Different battery data sets may contain varying characteristics and patterns of EV battery recycling, which will yield different parameter results when processing these data. These parameters reflect the importance and relationships of each factor within a specific data set, which can explore the universality of the GAT-based echelon utilization evaluation process. This implies that although the GAT-based evaluation method can effectively identify implicit relationships among parameters within a dataset, relying solely on a data-driven model for such a complex system as battery disassembly often overlooks the intricate mechanistic and physical constraints inherent to the battery. Consequently, this may lead to an incomplete and less accurate understanding of the deeper relationships among parameters. Therefore, it is essential to examine the inherent logics and rules of the characteristic relationships between the data nodes. This will enable more accurate and rigorous evaluation results, which requires incorporating knowledge-based evaluation methods and Petri networks to analyze the relevant characteristic factors through rule-based logic reasoning.

Although establishing rule-based logic reasoning requires certain a priori knowledge, to ensure this step does not reintroduce subjectivity, the foundational rules are not derived from arbitrary expert opinions but are strictly grounded in publicly available standards and a body of objective knowledge. This provides a transparent and objective basis for the knowledge reasoning framework. Furthermore, the GAT is not a traditional supervised learning classifier, it does not rely on any manually pre-set labels, but instead autonomously learns the weight parameters of battery characteristics directly from the graph-structured data. The obtained parameters can be used into the petri network relationship model, which can be calculated by the actual relationship between each characteristic factor. By comparing the acquired data with the original data, if the deviation from the original value falls within an acceptable range (less than 5 % is selected in this paper), the parameters can be reasonably verified. As shown in Fig. 5, it illustrates the integrated framework used for the reasoning and validation of battery evaluation parameters, which begins with the collection and preprocessing (including cleaning, transformation, integration, and reduction) of raw battery data to construct a high-quality feature dataset. This dataset is then input into the deep learning algorithm (GAT), which autonomously learns intrinsic data correlations to generate a set of initial dynamic weights (referred to as the processing data in the figure). Concurrently, a rule base, strictly grounded in industrial standards and objective physicochemical knowledge, provides logical constraints for the system. Both the processing data and the rule base are fed into the reasoning and decision making, which is embodied by the FPN. This core module validates the GAT's output against the predefined rules and optimizes it into a set of optimal parameters.

Evaluation analysis is a form of uncertain reasoning that can be used to infer uncertain results based on data calculation and relation mining. Multiple knowledge bases support the process reasoning to achieve

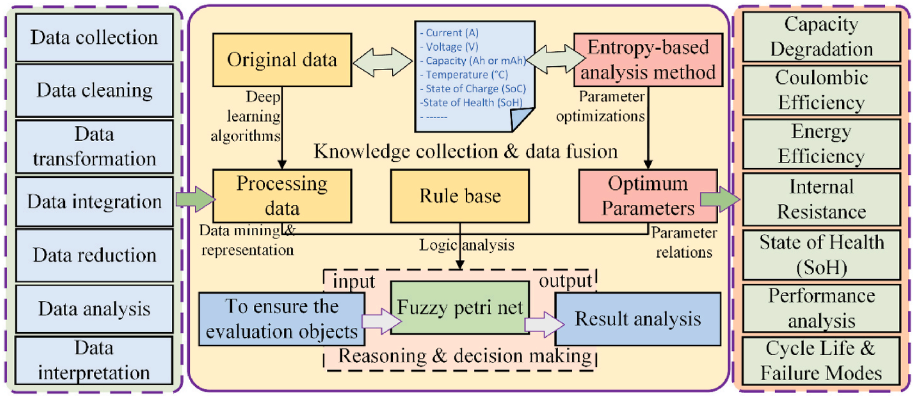

Fig. 5. The procedure of graph-based data and relation reasoning process.

optimal evaluation results, which are essential for ensuring the accuracy and reliability of knowledge reasoning. Therefore, it is necessary to propose a comprehensive and reliable knowledge-driven evaluation model with well-defined reasoning rules. The classic IF-THEN rule is proposed to construct the knowledge base (Zhou et al., 2019). For example, it is obvious to define that IF d_m, THEN F_m. Where d_m is a known judgement which serves as a starting point for reasoning (i.e.: as a pre-condition). F_m is the result of the judgement from the pre-conditions (i.e.: as a conclusion). A rule-based reasoning process can provide logical inferences, whether its precondition or conclusion includes multiple preconditions or multiple conclusions as shown in Fig. 6. Specifically, Fig. 6 (a) demonstrates a scenario where multiple conditions must be met simultaneously to derive a single result. In contrast, Fig. 6 (b) shows a reasoning process where a single condition leads to all possible conclusions. Fig. 6 (c) portrays a situation where any condition being met results in a single conclusion. Lastly, Fig. 6 (d) shows a case where a single condition leads to any of multiple conclusions. These variations represent different logical configurations for rule-based decision-making, where preconditions and conclusions may vary in complexity and interdependencies.

However, the rule base can be constructed according to the objective relations and related physical mechanism as shown in Fig. 7. A rule-based reasoning method not only require the use of all rule information to obtain the optimal evaluation results, but also selects the appropriate rules to determine the optimal reasoning outcomes based on the specific requirements of the recycling process. Based on the description and the image in Fig. 7, the diagram illustrates the rule-based reasoning process for assessing various characteristics of an EOL battery. Each step of the battery's lifecycle from its initial use to its module and pack-level analysis feeds into a system that evaluates

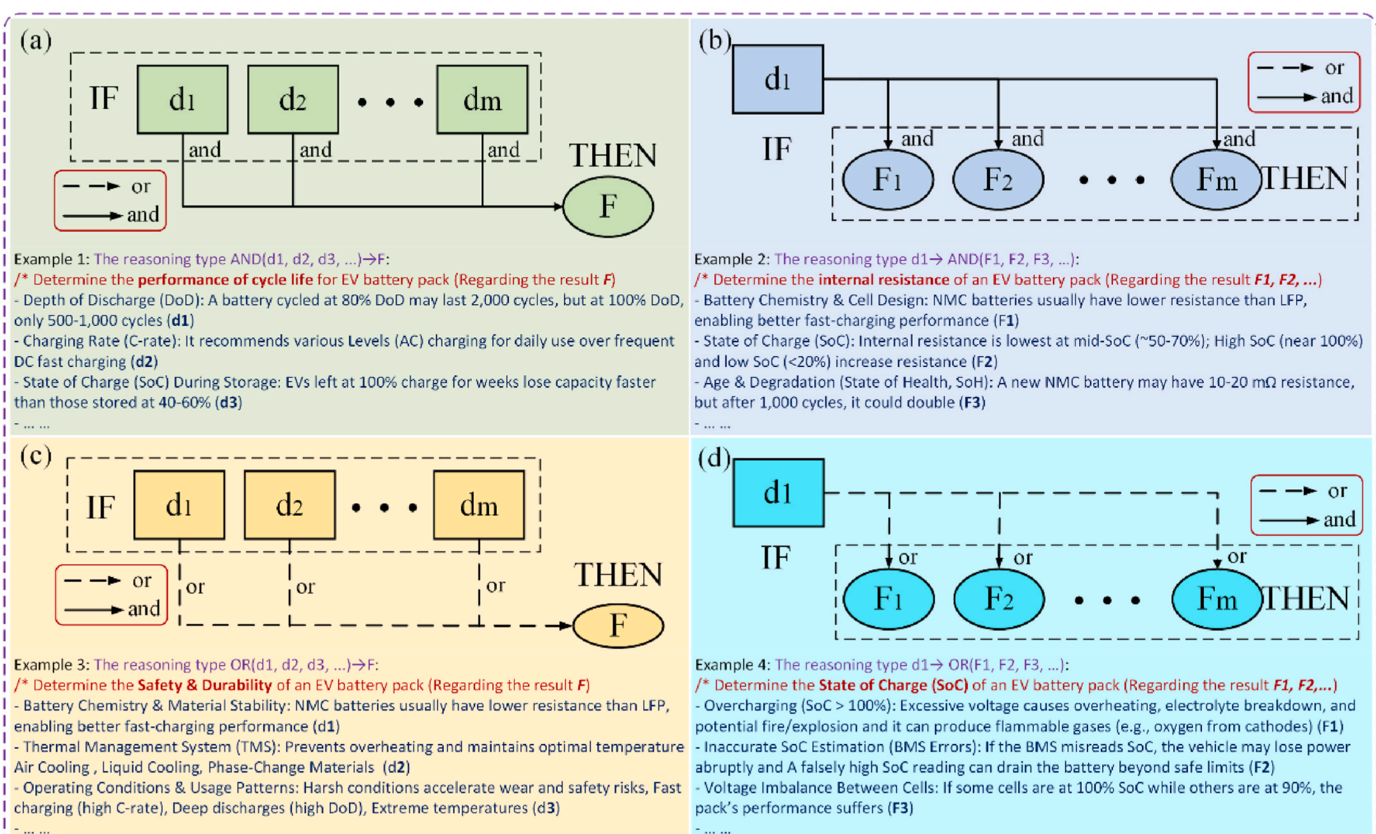

Fig. 6. Various reasoning types for composite rules-based knowledge evaluations.

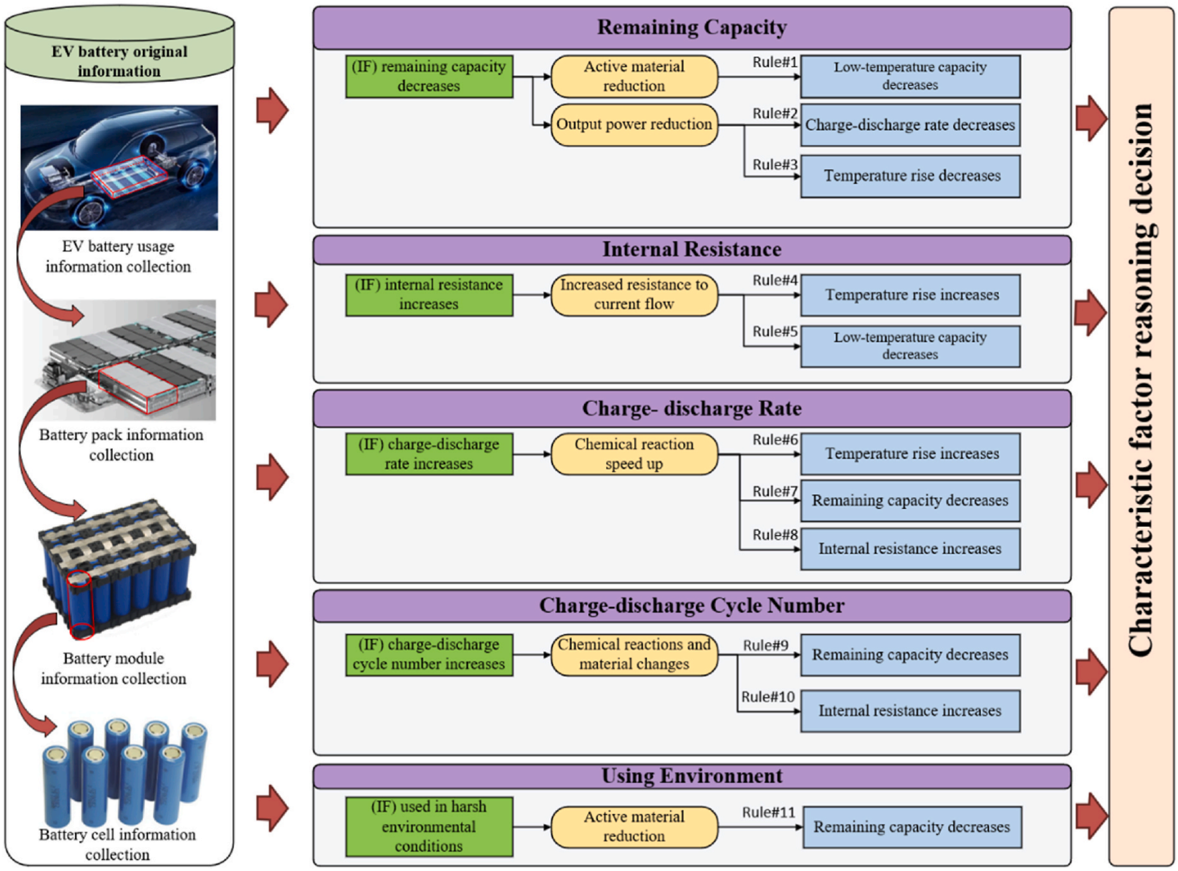

Fig. 7. The partially IF-THEN rules for EV battery characteristic relation reasoning.

different factors such as remaining capacity, internal resistance, charge-discharge rate, cycle number, and the working environment in which the battery is used. Each factor is governed by a set of rules, which outline the relationships between changes in one characteristic and its impact on others.

For example, an increase in internal resistance leads to higher temperatures, reduced remaining capacity, and worsened performance. The performance and degradation of retired EV battery packs are determined by the complex interplay between remaining capacity, internal resistance, charge-discharge rate, cycle number, and working environment. Similarly, the capacity fades and resistance increases with cycling, accelerated by high C-rates and extreme temperatures. The elevated charge-discharge currents generate excessive heat that accelerates electrode degradation, while environmental factors like temperature extremes and humidity further exacerbate aging. However, the retired EV battery packs can still find effective second-life applications when operated within moderate temperature ranges (20–30 °C), using conservative charge-discharge rates (below 0.5C), maintaining partial state-of-charge cycling (30–70 % SoC), and with continuous monitoring of rising internal resistance as a key health indicator, allowing for extended usability in less demanding applications like stationary energy storage systems.

Once the rule-based reasoning relationships are acquired based on the analysis requirements, they can be incorporated into *FPN* to achieve the optimal reasoning results. The *FPN* can be described as: $FPN = (P, T, D, \beta, \alpha, f)$ (Jiang et al., 2022), where $P = \{p_1, p_2, \cdots, p_m\}$ is a finite set of places; $T = \{t_1, t_2, \cdots, t_m\}$ is a finite set of transitions, The transition t_i connects two places, and the value of the transition w_i indicates the likelihood to transfer from the former into the latter. $D = \{d_1, d_2, \cdots, d_m\}$ is a finite set of preconditions, which is used to convert the rules into petri net; β is an associative function, $\beta(p_i) = d_i$ means that p_i corresponds to d_i , (In the evaluation of EV battery echelon utilization, d_i is the battery characteristic indicator, and p_i is the value of the characteristic indicator for a specific EV battery number); α is an associative function, $\alpha(p_i) = y_i, y_i \in [0,1]$, it indicates that the confidence degree of the p_i is y_i and $\alpha(t_i) = w_i$ indicates that value of the transition t_i is w_i. f is a calculation function in the logic operation, it is used to calculate truth degree of the p_i. In this paper, a Gaussian function $f_\alpha(x) = e^{-1.5(x-1)^2}$ is used for specific calculations. The calculation of p_i varies according to its position in the petri net. If p_i is at the beginning of the relationship network, $\alpha(p_i) = y_i, y_i \in [0,1]$, the value of y_i is the specific membership degree of p_i for the relevant evaluation level (i.e. $f(p_i) = \mu(p_i) = y_i$). If p_i is at the terminal position or intermediate transition position, $\alpha(p_{i-1}) =$

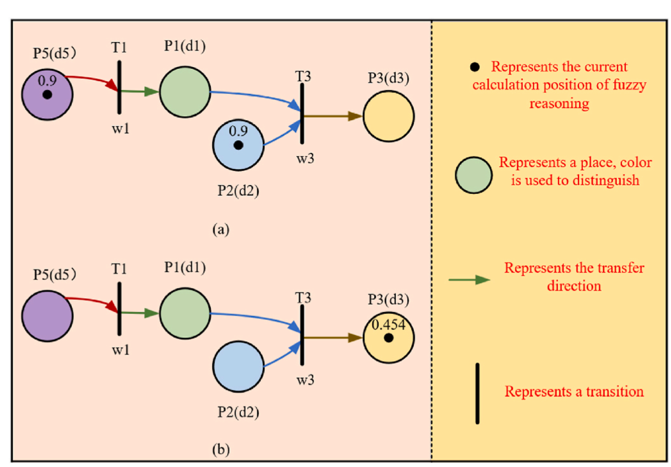

Fig. 8. The rule-based reasoning model based on FPN.

$y_{i-1}, y_{i-1} \in [0,1]$, $\alpha(t_i) = w_i, w_i \in [0,1]$, then $f(p_i) = f_\alpha(y_{i-1} \cdot w_i)$.

As shown in Fig. 8, it is important to explain the knowledge rules based on FPN in the context of logic reasoning. The petri net as shown in Fig. 8 (a) is transformed by the rule: {IF d_5 THEN d_1} (related to rule 7 in the knowledge base) and {IF d_1 and d_2 THEN d_3} (related to the combination of rule 2 and rule 5). According to the above rules it can be converted into a FPN by $D = \{d_1, d_2, d_3, d_5\}$ and $T = \{T_1, T_3\}$. The d_1, d_2, d_3, and d_5 respectively correspond to the remaining capacity, internal resistance rate, low-temperature capacity, and charge-discharge rate. The specific places represent the standardized values of the four characteristics factors of EV battery (The values are $\beta(p_1) = d_1, \alpha(p_1) = y_1$; $\beta(p_2) = d_2, \alpha(p_2) = y_2$; $\beta(p_3) = d_3, \alpha(p_3) = y_3$; $\beta(p_5) = d_5, \alpha(p_5) = y_5$). Transitions T_1 and T_3 represent the actions of d_5 changing to d_1, and the combination of d_1 and d_2 changing to d_3, respectively. At the starting position of p_i, the confidence degree y_i is the membership degree of p_i in the relevant evaluation level (Sáenz-Royo and Chiclana, 2025). In addition, p_i corresponds to the standardized value of the characteristic factors for EV battery packs, and its range is between 0 and 1. Furthermore, the value of p_i can be quantized to make subsequent calculations more efficient as shown in Table 3.

The transition represents the likelihood of moving from one place to another, and it depends on the relationships between the places. However, the weight a_i of each characteristic factor based on graph attention mechanism can determine the transition value. To verify the rationality of graph attention mechanism method, equation (4) can be used to convert the weight value in the logic reasoning process.

$$w_A = \frac{a_A}{\sum_{l=A}^{B} a_l} \tag{4}$$

As shown in Fig. 8, the confidence degree of the starting place p_5 and p_2 are respectively 0.9 and 0.9. For example, $\alpha(p_5) = y_5 = 0.9$, $\alpha(p_1) = y_1 = 0.9$), then we can get: $\alpha(p_1) = f_\alpha(y_5 \times w_1) = f_\alpha(0.9 \times 0.5572) = 0.6888$; $\alpha(p_3) = f_\alpha(y_1 \times y_2 \times w_3) = f_\alpha(0.9 \times 0.6888 \times 0.4428) = 0.4540$. The calculation value 0.454 is the confidence degree of place p_3 about a specific evaluation in the evaluation level set. To calculate the confidence results of p_3 for all evaluation levels through the above method, it is necessary to compare their evaluation values. The evaluation levels with the highest evaluation value represent the reasoning result obtained through logic reasoning. If the accuracy of the comparison result for a set of EV battery pack data exceeds 95 %, it indicates that the logic reasoning has been successfully completed.

4. Case study

The rule-based evaluation model can be used to analyze the actual echelon utilization applications for EV battery packs. The parameters of an individual battery from a set of EV battery packs can be evaluated using the above proposed model. The overall framework of the model can be demonstrated as shown in Fig. 9. The evaluated EV battery pack instances are tested by combining experimental instruments and factory data to obtain the relevant characteristic parameters. Appropriate parameters can be selected to establish the corresponding evaluation factor set and evaluation level set. The extracted characteristic parameters can be used to get the corresponding parameters through the graph attention mechanism and knowledge reasoning. Finally, the comprehensive evaluation method can be applied to select an appropriate membership function to construct the membership matrix, which is then calculated with the relevant parameters to derive the final evaluation result.

To verify the applicability of the evaluation model in assessing different types of EV batteries, this study selects three common EV battery types for experimental evaluation and analysis: 18650 lithium iron phosphate battery (LFP), nickel-cobalt-manganese ternary battery (NCM), and nickel-cobalt-aluminum ternary battery (NCA). The original parameters of these three battery types from various manufacturers are shown in Table 4, each exhibiting distinct characteristics and advantages. Firstly, LFP batteries are renowned for their excellent safety and long cycle life, with moderate specific energy and low self-discharge rates, making them suitable for applications with high safety requirements. NCM batteries, on the other hand, demonstrate superior overall performance, particularly excelling in specific energy, which makes them the preferred choice for electric vehicles. The NCA batteries, despite their high power density, exhibit certain limitations in cycle life and safety, necessitating cautious use in specific applications. To ensure the scientific validity, regulatory compliance, and industry comparability of our evaluation process, this study strictly adheres to the Chinese national standard, GB/T 34015.3–2021, titled by Recycling of traction battery used in electric vehicles – Echelon utilization – Part 3: Echelon utilization requirements. This standard serves as the authoritative technical document guiding the inspection and classification of retired EV batteries prior to echelon re-utilization in China. It provides detailed specifications for key technical indicators, testing methods, and judgment criteria regarding aspects such as appearance inspection, voltage and internal resistance consistency, and charge/discharge performance. In this study, the standard is specifically integrated into our methodology as follows.

- Establishment of the evaluation factor set: We leveraged the key performance parameters emphasized in the standard to select and define the characteristic factors for our evaluation model.
- Definition of the evaluation level set: The standard's classification of different performance levels provided a direct basis for setting the evaluation grades for various echelon utilization scenarios.
- Constraints for data generation: When generating simulated sample data, the parameter ranges specified in the standard were used as core constraints to ensure the realism and validity of the data.

To support the case analysis in this study, we have constructed a EOL battery dataset that is both realistic and representative. The construction of this dataset began with a high-quality basic dataset, which consists of two main components: (1) real-world historical data of retired batteries covering mainstream chemical systems such as LFP, NCM, and NCA, provided by industrial partners. This data includes factory specifications and BMS records; (2) standardized performance calibration tests conducted on physical battery packs, obtained from our partners, after passing safety checks such as corrosion, leakage, and deformation. These tests were carried out under standard laboratory conditions to acquire precise performance data. The basic dataset offers statistical distribution patterns of key performance parameters (e.g., capacity, internal resistance) for batteries at the end of life in the real world. In this analysis process, it is obvious to collect 20 samples for each of three types of EV battery packs based on computer random data according to the related

Table 3
The membership degree of the quantized value for each evaluation level.

Various standard status	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
Excellent	0	0	0	0	0	0	0.33	0.66	1	1	1
Good	0	0	0	0	0.33	0.66	1	1	1	0.66	0.33
Normal	0	0	0.33	0.66	1	1	1	0.66	0.33	0	0
Attenuation	0.33	0.66	1	1	1	0.66	0.33	0	0	0	0
Abnormal	1	1	1	0.66	0.33	0	0	0	0	0	0

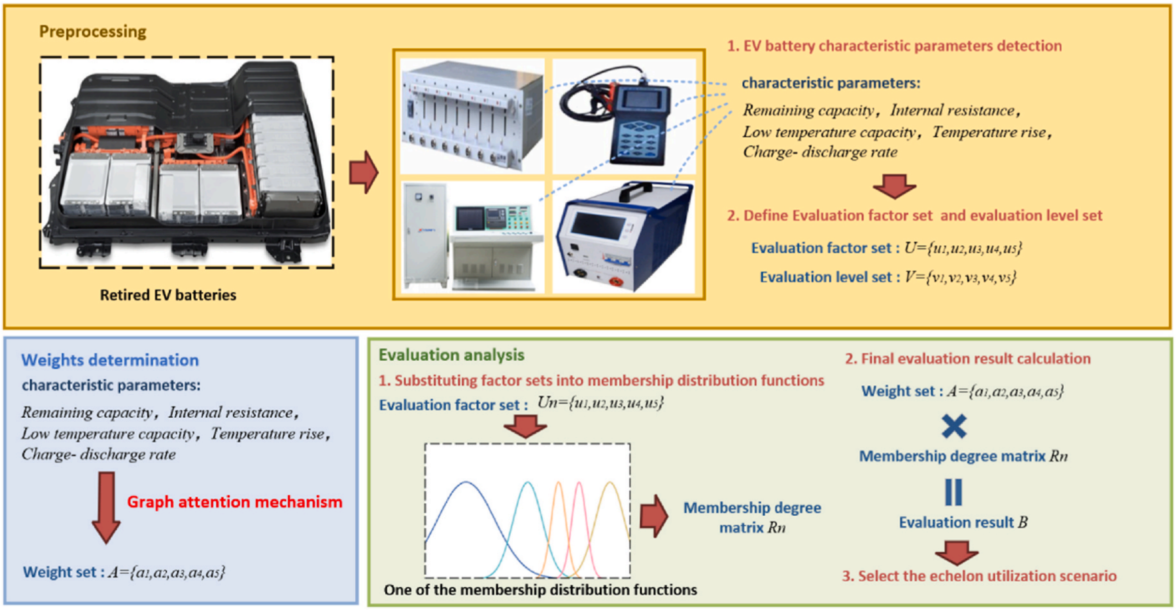

Fig. 9. The overall experiments and analysis process of rule-based comprehensive evaluation for EV battery packs or modules.

Table 4
Various evaluation levels for EV battery characteristics.

Battery product types	LFP	NCM	NCA
Energy density	90-120Wh/kg	150-220Wh/kg	200-260Wh/kg
nominal capacity	50-200Ah	50-250Ah	50-220Ah
Rated voltage	2.5–3.65V	3.0–4.2V	3.0–4.2V
Charging rate	1C	0.7–1C	0.7C
Discharging rate	1C	1C	1C
Discharge cycle	1000–2000	1000–2000	500

constraints and standards. By considering the testing samples, all generated EV battery packs underwent rigorous inspection, including disassembly and examination for issues such as corrosion, leakage, or deformation. Under strict safety protocols, it is significant to generated key parameter data of EV batteries through simulated testing and actual data provided by manufacturers, laying a solid foundation for subsequent evaluation and analysis.

Unlike traditional machine learning models where training, validation, and test sets are used for model training and evaluation, our approach is not designed to validate new battery characteristics or predict specific parameter values. Instead, it focuses on determining the influence weights of various battery characteristics, identifying how different factors contribute to the overall battery performance. As such, the concept of dataset partitioning into training, validation, and test sets does not apply in this context, as there are no specific outputs to validate or predict in the traditional sense. Instead, the data is used to model the relationships and dependencies between the battery parameters. The primary goal is to extract the relative importance of each feature (such as internal resistance, capacity, etc.) in influencing the overall battery performance and aging process. Therefore, all data in the dataset is utilized to derive these weights, without the need for separate training, validation, or testing phases.

4.1. Specific EV battery case analysis

It is necessary to define the evaluation factor set $U = \{u_1, u_2, \cdots, u_m\}$ and evaluation level set $V = \{v_1, v_2, \cdots, v_n\}$ for the EV battery. EV batteries may retire for various reasons (e.g., cycle aging, storage aging, overcharging/over-discharging). Distinguishing between different retirement scenarios would significantly increase the cost of screening and classification. Given that the performance parameters of EV batteries can directly reflect their condition regardless of the recycling cause, this study uniformly adopts the performance parameters as the evaluation factor set to streamline the assessment process with higher efficiency and more robustness. Various EV batteries might have various performance, such as battery capacity, internal resistance, charge-discharge voltage, rate discharge performance, high and low temperature capacity performance, mass specific energy, charge-discharge temperature rise and their cycle life. However, the testing of parameter performance requires time, economic costs, and safety considerations. In the industrial-scale recycling of retired EV battery packs, it is essential to ensure economic efficiency and personnel safety. Therefore, to scientifically and comprehensively select core evaluation indicators that best characterize the residual value and safety risks of EV batteries, and to provide a solid basis for the subsequent definitions of evaluation levels, this study adheres to the following selection principles:

- Critical Performance Characterization Capability: The selected indicators must directly and centrally reflect the battery current State of Health (SoH), potential Remaining Useful Life (RUL), and suitability for echelon re-utilization application scenarios. For instance, remaining capacity directly determines its value in energy storage and other echelon utilization scenarios, while internal resistance pertains to its power output capability, energy efficiency, and heat generation risk.
- Correlation with Aging Mechanisms and Failure Modes: The indicators should be closely related to the primary electrochemical aging mechanisms (i.e.: loss of active material, layer growth, lithium plating) and common failure modes of batteries, thereby enabling effective differentiation between batteries of varying health conditions.
- Feasibility and Cost-Effectiveness of Industrial Application: Considering the practical demands of large-scale screening, priority is given to parameters with mature testing methods, relatively short testing times, manageable equipment costs, and operational safety.
- Literature Support and Industry Consensus: The selection is informed by existing research in battery health assessment and echelon re-utilization, as well as by Key Performance Indicators (KPIs) widely recognized within the industry, ensuring the scientific validity and representativeness of the chosen indicators.

Based on these comprehensive considerations, combined with the contribution of each parameter to the overall battery performance and its discriminative power in practical echelon re-utilization screening, this paper ultimately identifies the following five characteristic factors as evaluation indices: battery remaining capacity, internal resistance, low-temperature capacity performance, battery charge-discharge rate capability, and charge-discharge temperature rise. The selection of the indicators aims to lay the foundation for constructing an accurate and reliable evaluation level system, thereby effectively guiding decisions on the echelon re-utilization and recycling of EV battery packs (Lai et al., 2021b).

- Battery remaining capacity is an incredibly significant characteristic in the echelon utilization evaluation of EV batteries, which can be used to demonstrate the normal usage, as well as the overall health status. In this paper, the rate of the current remaining capacity to the rated remaining capacity is defined as u_1. The evaluation criteria for the remaining capacity of retired EV battery packs are established based on a comprehensive analysis of relevant literature, industry standards, and practical engineering experience. By discussing and analyzing the capacity degradation curve of EV batteries, noting that the curve exhibits inflection points at the 80 % and 60 % nodes, corresponding to two critical failure mechanisms: electrolyte depletion (80 %) and active material phase transformation (60 %) (Atalay et al., 2020). Additionally, industry practices and field data indicate that batteries with capacities between 70 % and 80 % can still operate effectively in secondary applications. Integrating this related knowledge of the battery remaining capacity u_1, their evaluation levels can be defined as: 100 %> u_1 >80 % is recorded as excellent, 80 %>u_1 >70 % as good, 70 %>u_1 >60 % as normal, 60 %>u_1 >40 % as attenuation, and u_1 <40 % as abnormal.
- In addition, the internal resistance has a significant influence on the performance of EV battery and more energy loss if the internal resistance is high. The internal resistance of the battery will increase when the battery is gradually becoming aging. In terms of charging and discharging rate, a battery with a high internal resistance can suffer from a larger temperature rise, which might lead to safety issues. Considering the different internal resistance of each battery production, the specific value might vary at different temperature (Koc et al., 2022). In this study, the measurement of the internal resistance ratio strictly adheres to the ISO 12405–4:2018 standard. The measurements were conducted at a SoC of 50 % ± 5 % (within the stable open-circuit voltage region) to minimize polarization effects. A constant temperature chamber set at 25 °C (±0.5 °C accuracy) was used to eliminate environmental interference. To facilitate unification and calculation, the rate of the current internal resistance value to the resistance value of the new battery is marked as u_2, the smaller the internal resistance value, the better the health status of the battery. Based on the actual production data and theoretical references, which can be defined 1> u_2 >1.5 as excellent, 2>u_2 >1.5 as good, 2.5>u_2 >2 as normal, 3.5>u_2 >2.5 as attenuation, and u_2 >3.5 as abnormal (Sun et al., 2020).
- Low temperatures have a bigger influence on battery discharge than room temperature or higher temperatures, which will result in a considerable reduction in battery capacity (Na et al., 2021). According to the Low-temperature performance test standard in ISO 12405–4:2018, the batteries in this experiment were discharged at a constant current of 0.3C to the cutoff voltage in a −20 °C environment, and the ratio of the remaining capacity was recorded. The ratio of the battery capacity at low temperature to the rated capacity can be marked as u_3. Based on the actual production data and theoretical support, it is obvious to define the evaluation criteria for low-temperature remaining capacity as follows: 100 %> u_3 >80 % as excellent, 80 %>u_3 >70 % as good, 70 %>u_3 >60 % as normal, 60 %>u_3 >50 % as attenuation, and u_3 <50 % as abnormal (Liu et al., 2022).
- Furthermore, high temperatures have a significant risk of causing permanent degeneration of EV batteries, as well as deformation or rupture (Hamisi et al., 2022). Excessive temperature rise will result in excessive consumption and performance reduction for EV battery capacity, which was conducted in accordance with the ISO 12405–4:2018 and IEC 62660–2:2018 standards. Under the conditions of 25 °C ± 1 °C and an initial battery SoC of 50 % ± 5 %, temperature sampling was performed at the center of the cell surface during 1C constant current charge-discharge cycles. The temperature rise value of the battery at the 30-min mark of the discharge process was recorded as u_4. Based on the actual production data and theoretical support, it is obvious to define the evaluation criteria for temperature rise value as follows: The evaluation intervals of u_4 are: u_4 <4 °C is recorded as excellent, 6 °C> u_4 >4 °C as good, 8 °C> u_4 >6 °C as normal, 10 °C> u_4 >8 °C as attenuation, and u_4 >10 °C as abnormal (Li et al., 2024).
- The charge-discharge rate represents the speed of EV battery charging and discharging as well as the performance of its charge-discharge. The charge-discharge rate represents the ratio of the EV battery's charge-discharge capacity within a unit time to its rated capacity. The faster the charge-discharge speed, the greater the rate. In this study, the charge-discharge rate test was conducted in accordance with the ISO 12405–4:2018 standard. A constant current source (1C rate) was used to charge the battery to its rated voltage, followed by discharging it at the same rate to the cutoff voltage (e.g., 2.5 V) (Abavi-Torghabeh et al., 2023). The discharge time and capacity were recorded, and the ratio of the actual capacity to the rated capacity was calculated and defined as u_5.Based on the actual production data and theoretical support, we can define the related parameter values as follows: The rate of u_5 :100 %> u_5 >98.5 % is recorded as excellent, 98.5 %>u_5 >96 % is recorded as good, 96 %>u_5 >92 % is recorded as normal, 92 %>u_5 >85 % is recorded as attenuation, and u_5 <85 % is recorded as abnormal.

In short, the characteristic indicators can be defined as $U = \{u_1, u_2, u_3, u_4, u_5\}$, including the battery remaining capacity, internal resistance, low temperature capacity, charge-discharge temperature rise, and charge-discharge rate, respectively. Similarly, it is necessary to assess their performance by various evaluation levels, such as excellent, good, normal, attenuation, and abnormal, $V = \{v_1, v_2, v_3, v_4, v_5\}$ as shown in Table 5.

After determining the aforementioned indicators U and evaluation levels V, the experiments can be conducted based on 20 samples of EV batteries from three different types. The measurement methods for the battery performance parameters, as described earlier, are based on international standards and the Battery Test Manual for Plug-In Hybrid Electric Vehicles (Belt, 2010). The specific parameter data for these three types of EV batteries are described as shown in Fig. 10. Since directly analyzing the original data of EV battery characteristic parameters is challenging, the data values must be normalized. In the actual evaluation process, the evaluation factors (i.e., remaining capacity, low-temperature capacity, charge and discharge rate, internal resistance, and temperature rise) can be standardized through the complex reasoning and calculation so that the related data can be consistently dealt with. The obtained standardized data can be transferred to the proposed knowledge graph for evaluating echelon utilization factors. After the multiple iterations of graph attention mechanism, the similarity between the characteristic factors and the results can be acquired by the evaluation analysis. Consequently, leveraging the dynamic computation of the graph attention mechanism, the three different EV batteries yield distinct sets of parameter weights that reflect their unique parametric characteristics, as shown in Table 6.

Furthermore, it is necessary to acquire the weight coefficient of the characteristic factors by examining the specific process of comprehensive evaluation analysis. Different distribution functions (i.e.: trapezoidal distribution, k-order (k=*2,3*) parabolic distribution, and Gaussian

Table 5
Various evaluation levels for EV battery characteristics.

Evaluation levels	Remaining capacity	Internal resistance	Low temperature capacity	Temperature rise	Charge- discharge rate
Excellent	80 %–100 %	1–1.5	80 %–100 %	0–4 °C	98.5 %–100 %
Good	70 %–80 %	1.5–2	70 %–80 %	4–6 °C	96 %–98.5 %
Normal	60 %–70 %	2–2.5	60 %–70 %	6–8 °C	92 %–96 %
Attenuation	40 %–60 %	2.5–3.5	50 %–60 %	8–10 °C	85 %–92 %
Abnormal	0 %–40 %	>3.5	0 %–50 %	>10 °C	0 %–85 %

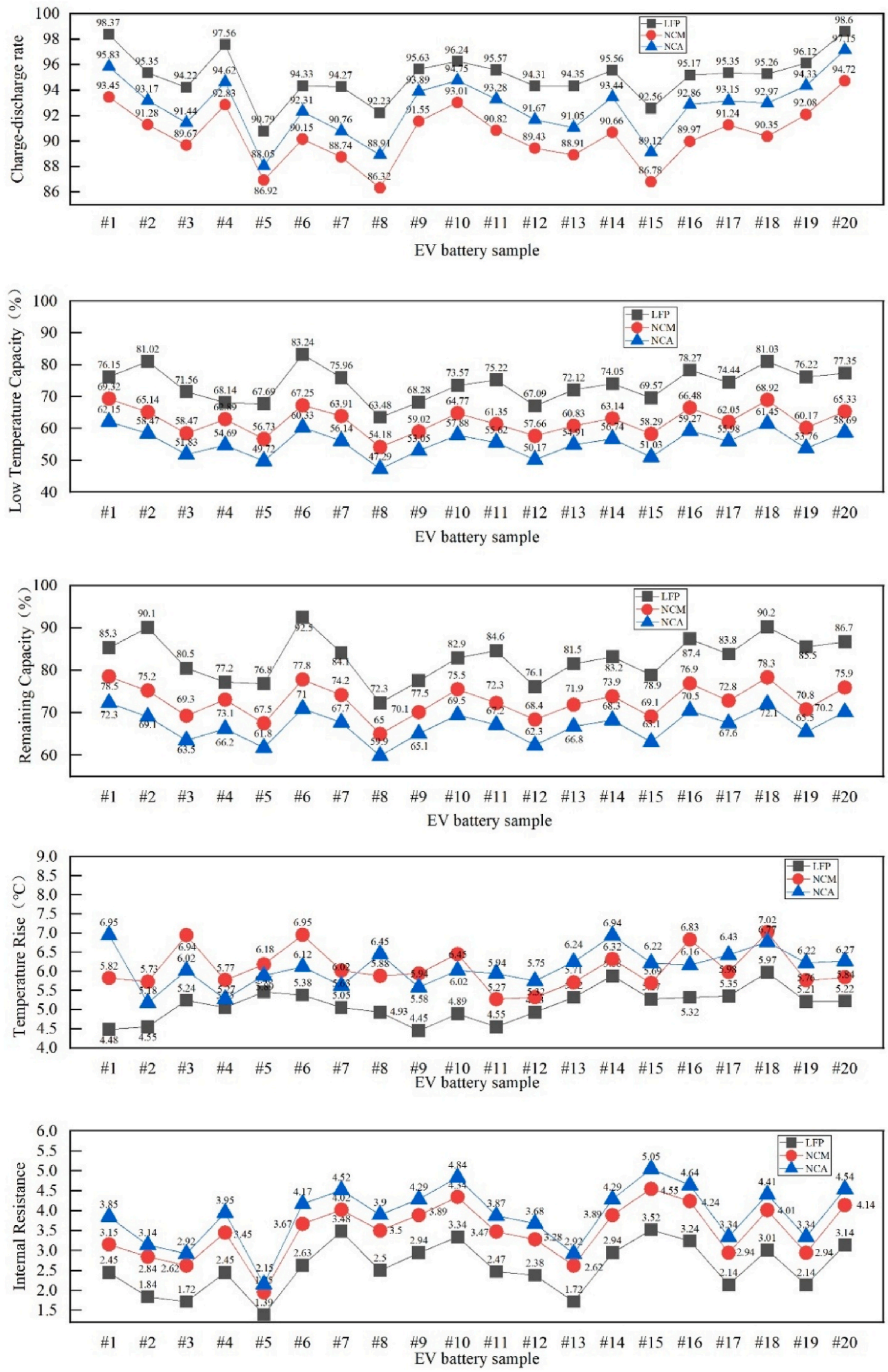

Fig. 10. The performance sample data of three different types of EV batteries for echelon utilization.

Distribution, etc. (Azadegan et al., 2011)) can be used to fit the membership degrees of individual battery characteristic factors, which can be selected for further calculations by comparing the differences between these different distributions. The properties of different distribution functions can meet the characteristic requirements of various EV battery packs. For instance, LFP batteries exhibit strong cycle stability and linear

Table 6
The weight of the characteristics for retired EV battery packs.

Battery types	Remaining capacity	Internal resistance	Low temperature capacity	Temperature rise	Charge- discharge rate
LFP	0.223	0.289	0.177	0.172	0.139
NCM	0.302	0.200	0.102	0.148	0.249
NCA	0.126	0.302	0.061	0.198	0.313

capacity degradation, making the trapezoidal distribution function more suitable for comprehensive evaluation. In contrast, NCM batteries show nonlinear capacity degradation and may experience the capacity "jump" phenomena, thus the 2-order distribution function is more appropriate for evaluating their remaining capacity. As for the internal resistance ratio, due to its typically high consistency, the Gaussian distribution function better reflects its characteristics.

The EV battery evaluation levels can be defined as Echelon I, Echelon II, Echelon III, Echelon IV, and Echelon V, which can be assigned to the five remarks: Excellent, Good, Normal, Attenuation, Abnormal. The membership degree of the specific characteristic value is from 0 to 1, which is different according to the selected distribution function. For example, when the battery remaining capacity u_1 is 62 %, the membership degree of Echelon III (Normal, 60 %–70 %) can be defined as 1 that the membership degree associated with Echelon IV (Attenuation, 40 %–60 %) can be defined as the specific distribution function. For the further Echelon V (Abnormal, 0–40 %), the membership degree can be defined as 0. Furthermore, the No.17 battery can be considered as an example that different evaluation functions can be used to acquire the corresponding evaluation matrix R. The results can be analyzed to select suitable distribution function. The remaining capacity u_1 of the No.17 battery is 75.44 %, its internal resistance rate u_2 is 2.14, its low-temperature capacity rate u_3 is 74.44 %, its charge-discharge temperature rise u_4 is 6.43 °C, and its charge-discharge capacity u_5 is 95.35 %.

After the data of the characteristic factors are normalized, they are substituted into the trapezoidal distribution comprehensive evaluation method with a value of 1. A_i represents the membership degree of the parameter to the Echelon levels. For the No.17 battery, the remaining capacity $u_1 = 75.44\%$, $A_1(u_1) = \frac{u-70\%}{80\%-70\%}$, $A_3(u_1) = \frac{80\%-u}{80\%-70\%}$, substituting into the equation, $A_1(u_1) = 0.5440$, $A_2(u_1) = 1$, $A_3(u_1) = 0.4560$ can be acquired. For internal resistance rate $u_2 = 2.14$, substituting into the equation, $A_2(u_2) = 0.7200$, $A_3(u_2) = 1$, $A_4(u_2) = 0.2800$ can be acquired. For low temperature capacity $u_3 = 74.44\%$, Substituting into the equation, $A_1(u_3) = 0.4440$, $A_2(u_3) = 1$, $A_3(u_3) = 0.5560$ can be obtained. For the charge-discharge temperature rise $u_4 = 6.43°C$, $A_2(u_4) = 0.7850$, $A_3(u_4) = 1$, $A_4(u_2) = 0.2150$. For charge-discharge rate $u_5 = 95.35\%$, $A_2(u_5) = 0.8375$, $A_3(u_5) = 1$, $A_4(u_5) = 0.1625$. The membership function of the trapezoidal distribution for residual capacity can be described as shown in Fig. 11(a).

The membership degree of the remaining characteristic factors can also be determined using the same method, allowing the construction of the logic relation matrix R_1 by using trapezoidal membership function. The matrix R_1 represents the degree of membership of various factors to different evaluation levels, with the values of the membership degrees regarding Excellent, Good, Normal, Attenuation, and Abnormal from left to right. Each row in the matrix represents the membership degree of the characteristic factors for different evaluation levels, corresponding to capacity, internal resistance rate, low temperature capacity, temperature rise, and charge-discharge rate from top to bottom. When the membership of the 2-order parabolic distribution function ($k=2$) is used,

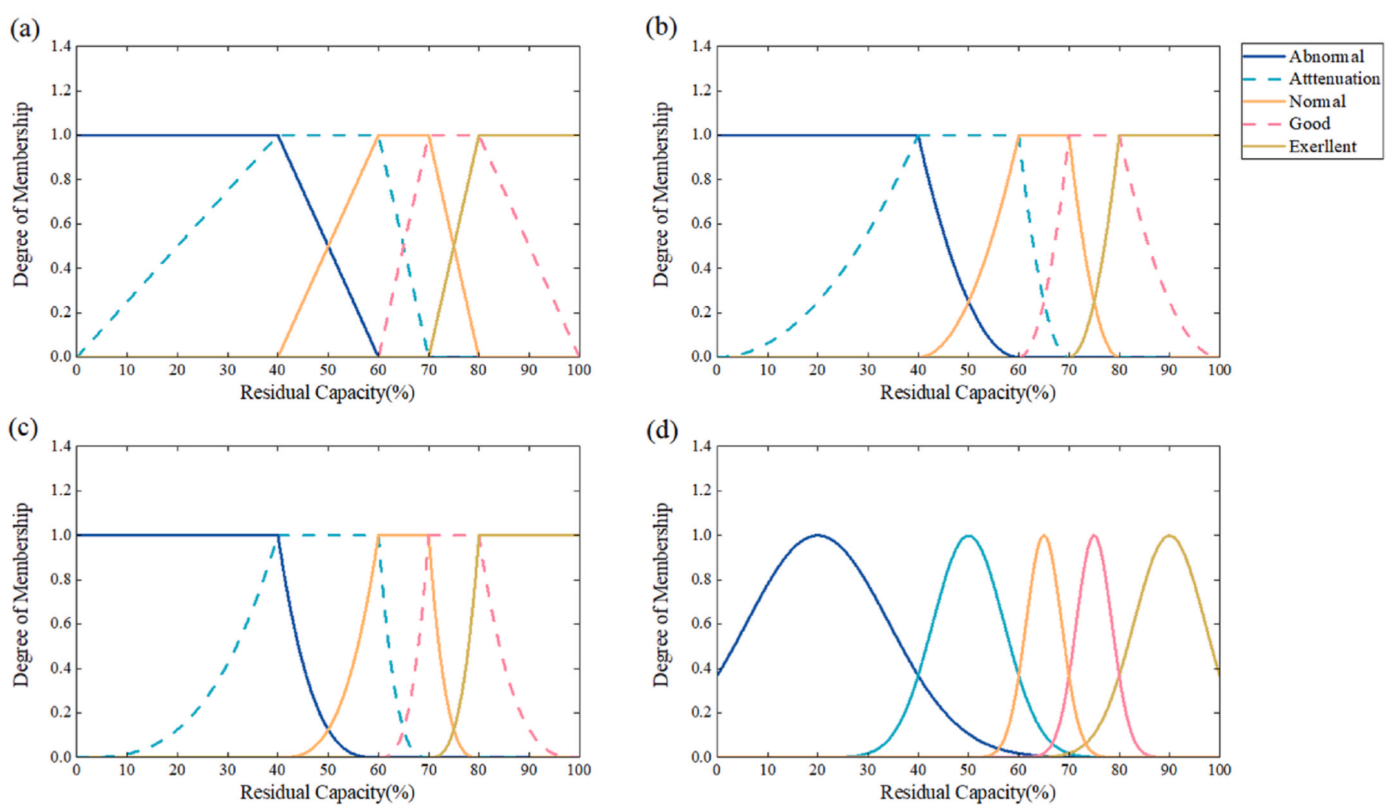

Fig. 11. The membership of four functions distribution of residual capacity. (a) Trapezoidal Distribution Function; (b) 2-order Distribution Function; (c) 3-order Distribution Function; (d) Gaussian Distribution Function.

the specific value is still substituted into the logic evaluation method through normalization to obtain the corresponding membership matrix R_2. The membership distribution of the second-order parabolic distribution function with respect to residual capacity can be described as shown in Fig. 11(b). When the 3-order parabolic distribution function (k=3) is used, the specific value are still normalized and then substituted into the evaluation method through normalization to obtain the corresponding membership matrix R_3. The membership distribution of 3-order parabolic distribution function with respect to residual capacity is shown in Fig. 11(c).The Gaussian distribution function can be used to deal with the relevant data of No. 17 batteries and then input them into the comprehensive evaluation method to determine the remaining capacity $A_1(u_1) = e^{-\left(\frac{u-90\%}{10\%}\right)^2}$, $A_2(u_1) = e^{-\left(\frac{u-75\%}{5\%}\right)^2}$, $A_3(u_1) = e^{-\left(\frac{u-65\%}{5\%}\right)^2}$. The related values $A_1(u_1) = 0.1200$, $A_2(u_1) = 0.9922$, $A_3(u_1) = 0.0128$ can be acquired. The characteristic factors of the EV battery packs have a relevant membership degree for each evaluation level. Similarly, the membership degree of each characteristic factor across different evaluation levels can be calculated to acquire R_4. For example, the residual capacity membership based on the Gaussian distribution can be described as shown in Fig. 11(d).

However, the weight $A = \{a_1, a_2, a_3, a_4, a_5\} = \{0.2231, 0.2893, 0.1772, 0.1717, 0.1387\}$ and matrices R_1, R_2, R_3, R_4 can be calculated by calculating the related characteristic factors to perform the normalization as the results B_i. The value B_i can be acquired by the comprehensive evaluation to assess the corresponding evaluation level. The trapezoidal, k-order ($k = 2$ and 3) parabola distribution function can be classified the battery No. 17 as an Echelon II (Good), and the Gaussian distribution function can be classified it as an Echelon III battery (Normal). Through the calculation demonstration of the comprehensive evaluation analysis for the aforementioned No. 17 LFP battery, we employed the same method to calculate all the battery data, obtaining their comprehensive evaluation results as shown in Fig. 12. The EV battery evaluation results need to be tested in practical application scenarios to verify the accuracy of the evaluation method and ensure the economic benefits and safety of

Table 7
Adaptability test parameters for echelon utilization scenarios.

Evaluation level	Echelon utilization scenarios	Cycle count qualification threshold	Test parameters (charge and discharge)	Recycling standards
Echelon I	Low-Speed Electric Vehicle	≥800 cycles	1C,25 °C	GB/T 34015-2017
Echelon II	Commercial energy storage	≥1500 cycles	2C,35 °C	UL 1974-2018
Echelon III	Grid energy storage	≥3000 cycles	0.2C,25 °C	IEC 62620-2014
Echelon IV	Household energy storage	≥500 cycles	0.5C,25 °C	JIS C 8715–2:2019

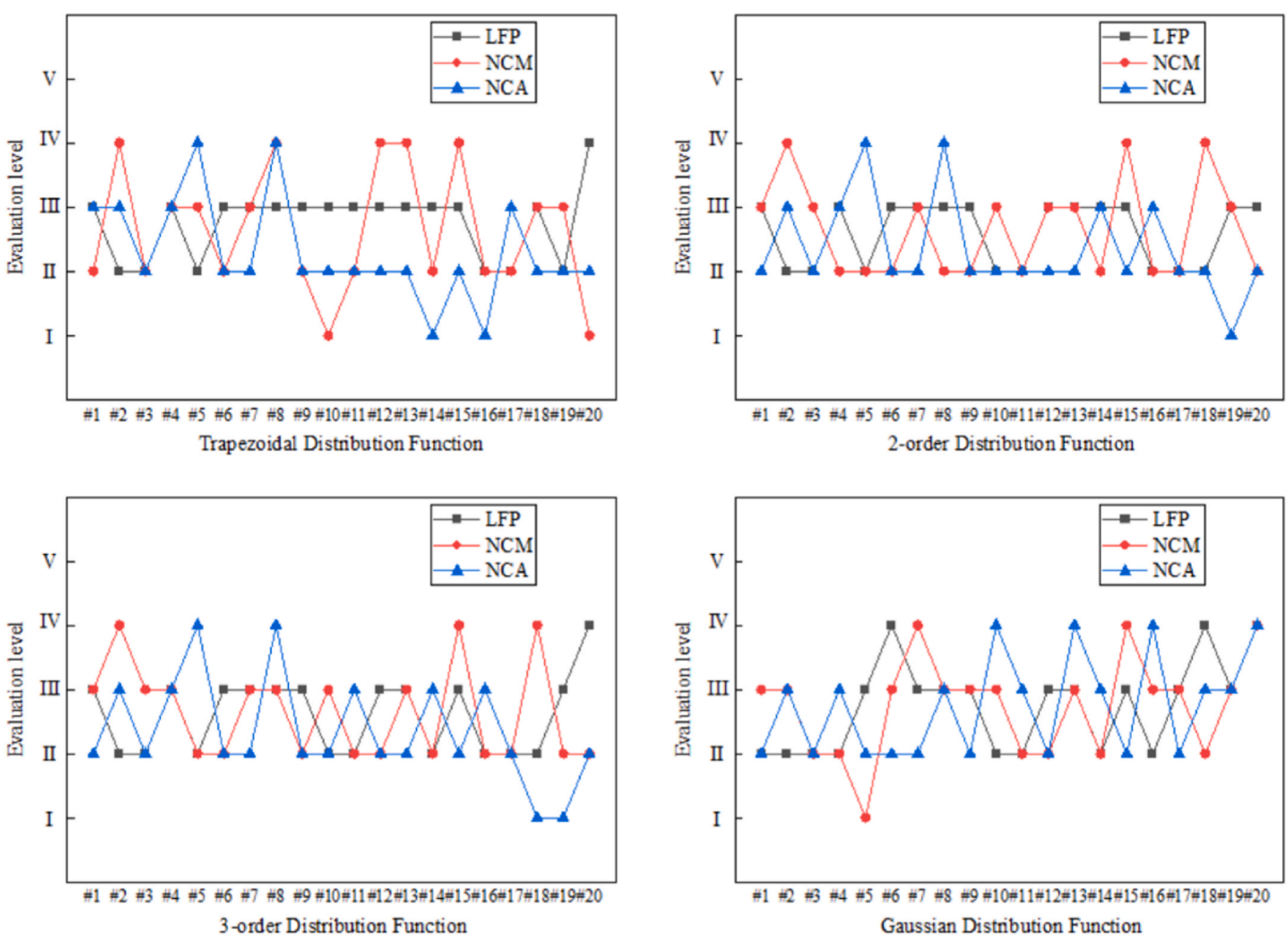

Fig. 12. Evaluation results of four distribution functions of each EV battery.

battery echelon utilization. To simulate this practical effect, we selected appropriate charge-discharge test parameters based on the echelon utilization scenarios corresponding to each evaluation level as shown in Table 7. Subsequently, the experimental batteries were subjected to charge-discharge cycle tests under the corresponding evaluation scenarios according to the test parameters. The actual number of charge-discharge cycles was recorded and compared with the theoretical qualified cycle count, thereby calculating the accuracy of the evaluation results and the safety of the batteries.

The evaluation accuracy was calculated through the following procedure: Firstly, the actual charge-discharge cycle counts of experimental batteries in corresponding evaluation-grade scenarios were recorded and divided by the pre-determined cycle count threshold to obtain individual battery evaluation accuracy. For the EV batteries of the same type, the comprehensive evaluation accuracy under specific allocation functions was ultimately determined by summing the accuracy values of all individual batteries and dividing by the total number of EV batteries. As shown in Table 8, comparative results are presented showing the evaluation accuracy of three battery types under different comprehensive evaluation allocation functions.

The accuracy of calculation method not only quantifies the performance of individual EOL battery under specific evaluation scenarios but also allows verification of its applicability through comparative analysis of different battery product types. In this study, three distinct types of EOL batteries exhibited consistent and reasonable accuracy distributions under various comprehensive evaluation allocation functions, further demonstrating the method effectiveness and reliability in multi-type battery evaluations. The experimental results indicate that the selection of comprehensive evaluation allocation functions exhibits significant dependence on different battery chemistries. Specifically, LFP batteries demonstrate optimal evaluation performance under the trapezoidal allocation function, achieving a grade accuracy of 93.56 %. This is attributed to the highly stable aging characteristics of LFP batteries, where their capacity degradation curves follow a nearly linear trend, aligning well with the linear decay assumption of the trapezoidal function. In contrast, NCM and NCA batteries achieve accuracies of 94.62 % and 92.57 %, respectively, under the third-order allocation function. This advantage stems from the nonlinear degradation features observed in these ternary material batteries during aging. Although NCM/NCA systems exhibit excellent initial performance, they are prone to sudden failure mechanisms such as layer rupture and particle cracking in the later stages of cycling. The non-stationary degradation behavior is physically consistent with the multi-stage decay model of the third-order function. This mechanistic difference highlights that the selection of an appropriate distribution function should be based on their aging characteristics for improving the accuracy of echelon utilization evaluations.

4.2. Evaluation analysis based on rule-based reasoning

The rule-based evaluation analysis combined with the graph attention mechanism can be used to obtain the optimal parameters that can only be applicable to the data analysis of EV battery packs. This feasibility analysis of the proposed method can be used to verify the correctness of the parameters through logic reasoning. When performing rule reasoning between characteristic factors of retired EV battery packs,

Table 8
The accuracy of evaluation results for LFP, NCM, and NCA batteries under different distribution functions.

Distribution function	LFP	NCM	NCA
Trapezoidal Distribution Function	93.56 %	89.67 %	87.29 %
2-order Distribution Function	90.11 %	92.36 %	91.44 %
3-order Distribution Function	89.83 %	94.62 %	92.57 %
Gaussian Distribution Function	82.91 %	73.64 %	84.94 %

a single rule only represents the relationship between two characteristic factors. However, this simple relationship cannot adequately capture the parameter analysis, as it overlooks the complex coupling between all the related characteristic factors. Therefore, the relationship between the five characteristic factors can be constructed according to the knowledge base as shown in Fig. 13(a), where X_1, X_2, X_3, X_4, X_5, and X_6 represent the remaining capacity, internal resistance rate, low-temperature residual capacity, temperature rise, charge-discharge rate, and charge-discharge times. The solid-line connection represents positive feedback, and the dotted-line connection indicates negative feedback. This distinction is particularly important for subsequent rule propositions and membership calculations. As shown in Fig. 13(a), it provides a visual representation of the knowledge base, making it easier and more intuitive to recognize the interrelationships between various characteristic factors of the specific EV battery packs. By combining with Figs. 7 and 13(a), all the related rules (i.e.: Rule #3, Rule #4, Rule #7 and Rule #8) can be selected to build the logic relations, such as {IF d_5, THEN d_1}, {If d_5^*, THEN d_2} and{ IF d_1 and d_2, THEN d_4}. Thus, the FPN can be obtained as shown in Fig. 13(b). d_1, d_2, d_4 and d_5 are the preconditions of specific logic reasoning, and p_1, p_2, p_4, and p_5 are the values of the corresponding characteristic factors of specific EV batteries.

By considering No. 1 battery as an example, the standardized values after quantification are $p_1 = 0.1$; $p_2 = 0.5$; $p_4 = 1$; $p_5 = 1$. Since the logic reasoning result of the temperature rise (X_4) needs to be determined at the end, and X_4 belongs to the excellent evaluation level, the proposition can be specified as follows: (1) If d_5 (the charge-discharge rate is small), then d_1 (the remaining capacity will keep a better status); (2) If d_5^* (the charge-discharge rate is higher), then d_2 (the internal resistance rate is smaller); (3) If d_1 and d_2, then d_4 (the temperature rise is small). The reason for condition d_5 and d_5^* seems to be a paradoxical event that the charge-discharge rate needs to balance the roles between the remaining capacity and the internal resistance rate. By considering the data set of related membership degrees for the original data derived from EV battery characteristics, as shown in Table 3, a more accurate and comprehensive evaluation of battery status can be achieved. The truth degree of the related conditions can be acquired: $\beta(p_5) = d_5$, $\alpha(p_5) = y_5 = 0$, $\beta(p_5^*) = d_5^*$, $\alpha(p_5^*) = y_5^* = 1$. By calculating equation (4) can obtain the weight results $w_1 = \frac{a_1}{a_1+a_2+a_4+a_5} = 0.2711$, $w_2 = 0.3516$, $w_4 = 0.2087$, $w_5 = 0.1686$. Then, it can obtain the truth degree of the logic reasoning result based on FPN: $\alpha(p_1) = f_\alpha(y_5 \times w_1) = f_\alpha(0 \times 0.2711) = 0.2231$; $\alpha(p_2) = f_\alpha(y_5^* \times w_2) = f_\alpha(1 \times 0.3516) = 0.5322$; $\alpha(p_4) = f_\alpha(y_1 \times y_2 \times w_4) = f_\alpha(0.2231 \times 0.5322 \times 0.2087) = 0.2401$.

The final evaluation levels (i.e.: Good, Normal, Attenuation, and Abnormal) can be obtained as 0.233, 0.230, 0.232, 0.237. Battery No. 1 yields the inference results based on the FPN, demonstrating that the battery temperature rise corresponds to the *Excellent* level, thereby confirming its reliability. The original temperature rise data of No. 1 EV battery can be selected as the *Excellent* level, which means that the inference results based on rule reasoning are in line with the original data. By calculating the logic reasoning results for the temperature rise of each EV battery and comparing them with the original data, it is found that the logic inference results are fully consistent with the original data, achieving an accuracy of 100 %. It shows that the graph attention mechanism and logic reasoning model are still feasible and accurate. Therefore, it can be concluded that the parameters derived from the analysis of a specific data set using the graph attention mechanism can be effectively used to evaluate the echelon utilization of the corresponding EV battery.

4.3. Comparative analysis

To demonstrate the influence of GAT and FPN on the evaluation methodology, two comparative configurations are introduced: a GAT-

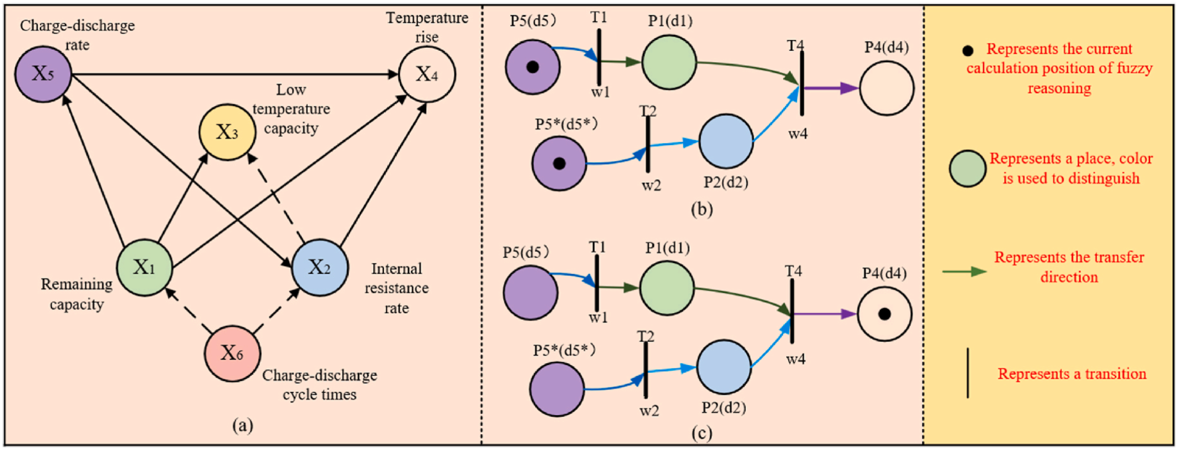

Fig. 13. The relationship of EV battery characteristic factors (a) and FPN with initial state (b) and reasoning results (c).

only method, in which the rule-based FPN stage is removed and the final assessment is obtained by directly aggregating membership scores with the data-driven weights learned by GAT; and an FPN-only method, in which the GAT-derived weights are replaced by entropy-based weights while the FPN reasoning is retained. By evaluating these configurations against the complete framework, the marginal and joint contributions of the two components can be quantified. Using the GAT-only and FPN-only methods, the corresponding characteristic weights are computed separately for the three retired EV battery types, and the results can be presented as shown in Table 9. The obtained weights are subsequently applied in the comprehensive evaluation. To control variables across the comparative experiments, the distribution function can be fixed to the third-order formulation for all methods. The corresponding evaluation results are presented in Fig. 14. The evaluation results are assessed using the same procedure described in Section 4.1 to measure the accuracy under the practical application scenarios, while the outcomes can be demonstrated as shown in Table 10.

Across the three battery types, the complete framework GAT-FPN attains the highest accuracy (LFP = 89.83 %, NCM = 94.62 %, NCA = 92.57 %), while removing either component degrades performance—moderately for the GAT-only (83.51 %, 87.93 %, 84.90 %) and more markedly for the FPN-only (72.43 %, 74.84 %, 70.69 %). These results are consistent with the roles of the two methods: GAT is data-driven and captures the contribution of each battery characteristic under different chemistries, while FPN emphasizes physics- and rule-based consistency, constraining the evaluation to follow known monotonicities and safety relationships. Without GAT, the system loses the ability to analyze weights dynamically and becomes less discriminative across chemistries; without FPN, the evaluation may deviate from physical plausibility. The observed accuracy declines quantify their complementarity and confirm that both GAT and FPN are necessary for battery evaluation.

4.4. Battery echelon utilization scenarios

According to the GB/T 34015.3–2021 standard, the application scenario for battery echelon utilization will be analyzed to evaluate the specific characteristics of EV battery packs. These evaluations can then be applied to corresponding application scenarios as shown in Fig. 14. By calculating the evaluation characteristic factors, it is essential to determine the appropriate echelon utilization scenarios corresponding to the five evaluation levels. When the logic comprehensive evaluation level recommends the application scenario of Echelon I, and the membership degree of the five characteristic factors of the EV battery fall under the Echelon I (i.e. Excellent), it indicates that the battery exhibits outstanding overall performance. Such EV battery packs are suitable for scenarios requiring exceptionally high battery performance, such as backup power supply for communication base stations.

As shown in Fig. 15, the comprehensive evaluation level of EV batteries recommends Echelon I. However, the membership degrees of the five characteristic factors are not all in Echelon I. However, it is necessary to evaluate the battery characteristics to determine their suitability for use in low-speed EV batteries or in applications with higher comprehensive performance requirements. When the comprehensive evaluation level recommends Echelon II, the EV batteries can be considered to have good performance, still meeting the requirements of certain high-performance application scenarios, such as grid peak shaving services or commercial energy storage and emergency power supply. When the comprehensive evaluation level recommends Echelon III, the EV battery can be used in various scenarios, such as grid energy storage service or electric vehicle charging stations, where the performance requirements are relatively low. When the comprehensive evaluation level recommends Echelon IV, it indicates that the EV battery performance has deteriorated to the point where it is no longer suitable for commercial or industrial use.

However, it can still be repurposed as a residential energy storage device. Household energy storage has a modest demand on the battery overall performance, which might be supplied by employing the Echelon IV for EV battery. Finally, when the battery comprehensive evaluation level falls under Echelon V, it signifies that one or more aspects of the battery's health status are abnormal. The battery is unsuitable for general echelon utilization from an economic or a safety standpoint. It

Table 9
Characteristic weights for retired EV battery packs under comparative analysis.

Application analysis approaches	Battery types	Remaining capacity	Internal resistance	Low temperature capacity	Temperature rise	Charge- discharge rate
GAT-only	LFP	0.251	0.259	0.181	0.151	0.158
GAT-only	NCM	0.331	0.179	0.101	0.121	0.268
GAT-only	NCA	0.111	0.301	0.061	0.169	0.358
FPN-only	LFP	0.219	0.321	0.141	0.221	0.098
FPN-only	NCM	0.178	0.281	0.101	0.259	0.181
FPN-only	NCA	0.121	0.338	0.076	0.281	0.184

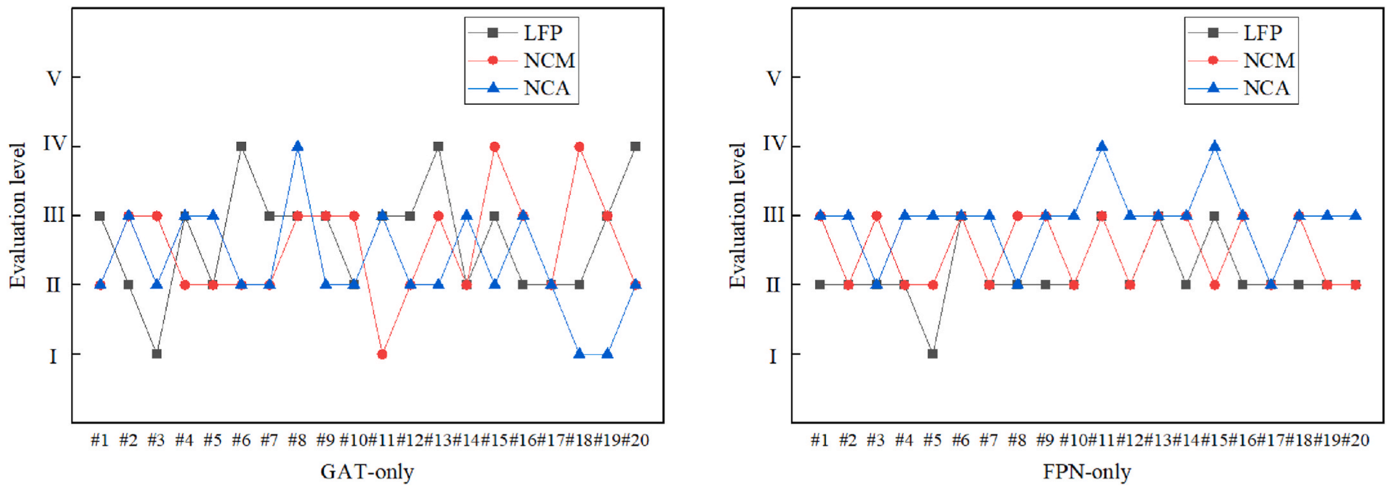

Fig. 14. The evaluation results for each EV battery pack under comparative methods.

Table 10
The accuracy of evaluation results for LFP, NCM, and NCA batteries under comparative methods.

Distribution function	LFP	NCM	NCA
GAT-FPN	89.83 %	94.62 %	92.57 %
GAT-only	83.51 %	87.93 %	84.90 %
FPN-only	72.43 %	74.84 %	70.69 %

should provide the material recycling rather than the battery echelon utilization. It is inevitable that some special worn EV battery packs may show up during a comprehensive evaluation, which is closely related to their operating environment and usage patterns. For example, while most of the characteristic factors of retired EV batteries may reach Echelon I, a few factors could fall under Echelon III or lower. In such cases, special attention needs to be given to the lower-performing factors of EV batteries when considering practical echelon utilization applications.

In addition to general echelon utilization scenarios, there are often specific scenarios in practical applications where certain battery parameters are given more attention due to environmental factors or operational habits. For instance, in high or low-temperature environments, the thermal characteristics of the battery (such as the rate of temperature rise and thermal stability) become critical considerations. In high-power demand scenarios, the power output capability and internal resistance characteristics of the battery are particularly important. Moreover, involving frequent charge-discharge cycles, the cycle life and capacity degradation characteristics of the battery receive significant attention. Therefore, in specific scenarios, certain battery parameters are emphasized, which necessitates a comprehensive consideration of the complex coupling relationships between these specific factors during logic reasoning and parameter analysis. Additionally, the weights of performance parameters should be reasonably assigned based on the requirements of specific scenarios to ensure the accuracy and adaptability of the evaluation analysis.

5. Discussion

Considering the challenges associated with the evaluation and selection of application scenarios for EV batteries in echelon utilization, the authors present a dynamic hybrid graph attention mechanism combined with an evaluation approach in the paper. The proposed method offers the following advantages.

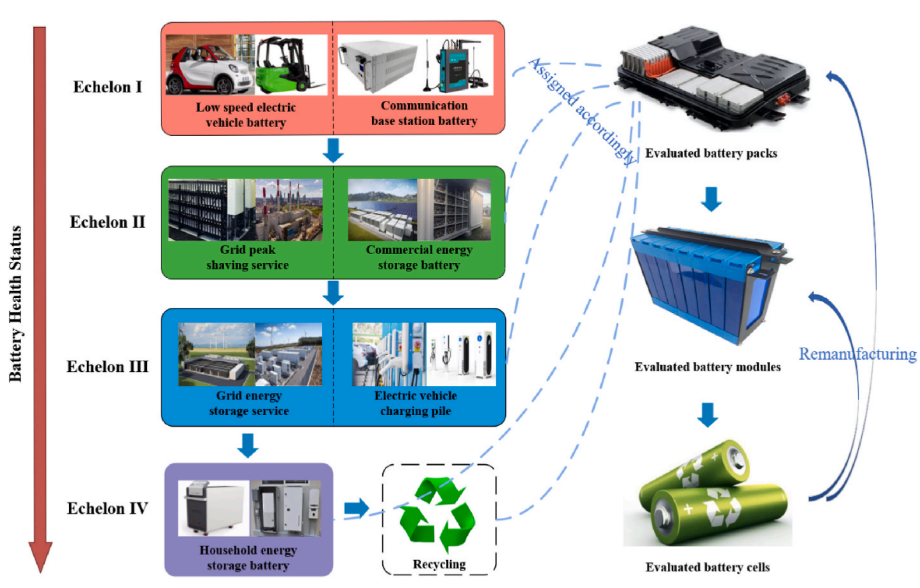

Fig. 15. Various application scenarios for echelon utilization of EV battery packs.

- Firstly, as to the solution to the needs of EV battery health evaluation for the specific echelon utilization scenarios, the proposed evaluation approach offers designers with a framework to determine the basic architecture of EOL battery based on the evaluation system. When dealing with the uncertainty of EOL batteries, a unified evaluation criterion can be employed to select and assess the relevant characteristics of the batteries. Moreover, the framework offers designers an effective method for selecting and determining battery characteristic factors in the evaluation system, significantly improving the efficiency of establishing the battery evaluation system for the potential echelon utilization for EOL battery in the future recycling application. Our proposed framework, by contrast, directly addresses this limitation that provides designers with a clear and efficient method for selecting and defining key battery characteristic factors through a more formalized procedure, and for applying unified evaluation criteria accordingly. The ultimate effect is a significant reduction in the complexity and subjectivity associated with building an evaluation system from scratch for different echelon utilization scenarios, thereby substantially enhancing the overall efficiency of deploying new assessment systems in future recycling applications.
- Secondly, the authors propose the evaluation approach in which the echelon utilization scenarios of EV batteries can be directly derived from data input to the final evaluation results. In this rule-based evaluation method, a combination of graph attention mechanisms and comprehensive assessments is used to analyze the feasibility of various echelon re-utilization applications. This method not only eliminates the subjectivity of the evaluation method but also consider the more internal relationship between the relevant characteristic factors of EOL battery packs. This method can generate a set of parameters specifically for each battery group based on the uncertainties of the retried EV battery characteristics and structure. It allows for verification through logic reasoning, achieving a dynamic evaluation of EOL battery packs. When dealing with different EV batteries, the proposed evaluation method can capture their distinct characteristics, enabling better selection of echelon utilization scenarios. In the case study with LFP batteries, the graph attention mechanism captures the weak correlation between the remaining capacity and the internal resistance, accurately determining that although the battery is no longer suitable for high-power driving scenarios, it still holds significant value in lower-capacity storage systems or backup power sources due to its high safety. For high-energy-density NCM/NCA batteries, the method identifies the strong correlation between the internal resistance and the charge-discharge rate, which allows the model to recommend more conservative echelon utilization scenarios with lower discharge rates. The fine-tuned evaluation capability of the method enables precise matching of appropriate batteries to scenarios that maximize their residual value, avoiding resource misallocation and waste caused by incorrect assessments. This has profound implications for the entire battery recycling market.

However, although the authors' research team has applied the proposed evaluation approach successfully to the echelon utilization scenario of EV battery, several perspectives for future research based on this approach are still recommended.

- With the rapid development of EVs and the continuous expansion of the market scale, the need for recycling EV batteries is growing, leading to a surge in demand for EV battery evaluation [41]. In this new and challenging context, improving the efficiency and accuracy of evaluation is a critical development requirement. The determined the parameters, however, are only applicable to this specific set of data. The weight data of a new group of EV batteries needs to be re-determined when faced with a large number of battery packs, which will inevitably lead to a significant increase in repetitive workload. Future research could therefore focus on the scalability of the evaluation model, for instance, by exploring the use of distributed computing frameworks to parallelize computationally intensive tasks such as data preprocessing and feature extraction, thereby greatly optimizing the efficiency of model training and inference.
- Echelon utilization of the EV battery is a promising industrial application due to its significant potential for generating both economic and environmental value. In this study, based on national standards and industry practices, we propose a five-level hierarchical framework for echelon utilization evaluation. This hierarchical structure provides a clear and standardized exploratory framework for complex echelon utilization evaluations. However, such a relatively fixed classification also raises a more critical decision-making issue in practical commercial applications. For example, when a battery serving in a low-speed vehicle (Echelon I) no longer meets the performance requirements of that scenario due to degradation, a key question arises: should it be directly retired for recycling, or should it be transferred to a less demanding application, such as grid energy storage (Echelon III), based on its remaining state of health? The echelon utilization of batteries is a complicated process that requires the considerations of the criteria, policies, regulations, markets, costs, and values to effectively balance the specific application scenarios. It is crucial to consider practical factors, such as economic benefits and safety, during the battery echelon utilization process. The proposed evaluation approach analyzes the influence of the internal characteristics of EV battery under idealized conditions. However, the specific application of echelon utilization scenarios must take into account various practical aspects such as economic feasibility and security. Therefore, the future work should focus on constructing a multi-objective optimization method for EV batteries that integrates both economic viability and safety, thereby enabling a comprehensive evaluation for echelon re-utilization that accounts for all influencing factors.
- Although a full life cycle assessment (LCA) is outside the scope of this work, it is important to situate the proposed evaluation within an environmental context. In general, reuse and repurpose strategies retain product function and embedded value, thereby avoiding impacts linked to primary material extraction, cathode/anode manufacturing, and cell production. By contrast, recycling primarily delivers material recovery benefits and may involve energy-intensive processing; its net advantage depends on the recovered yield and the displaced primary materials. The environmental outcome of a specific echelon choice is context-dependent, influenced by remaining capacity and efficiency, internal resistance and thermal behavior, expected duty cycles, and the carbon intensity of the electricity mix in the target application. In future work, the evaluation framework could be coupled with life-cycle-based decision support, for example by associating each recommended echelon level with indicative impact factors and by propagating uncertainty ranges. Such integration would enable multi-criteria decisions that jointly consider technical feasibility, safety, economic performance, and environmental benefits.
- The proposed evaluation framework can serve as a practical decision-support layer for emerging regulatory schemes governing second-life batteries. By combining data-driven weighting with rule-based reasoning, the tool translates technical measurements into traceable, standards-aligned judgments that are compatible with existing guidance for echelon utilization (e.g., classification and testing logic consistent with GB/T 34015.3–2021) and repurposing/stationary deployment practices (e.g., UL, 1974; IEC 62620). In practice, the outputs, including weights, membership matrices, and rule-consistent evaluation levels, can be archived as audit-ready evidence to support conformity assessments, safety documentation, and due-diligence checks across reuse/repurpose pathways.

6. Conclusion

This study successfully developed and validated a dynamic hybrid graph attention mechanism to address the core challenges of complexity and subjectivity in evaluating EV batteries for echelon re-utilization. The research achieved its primary objectives through two main contributions. Firstly, we established an efficient and systematic evaluation framework that replaces the cumbersome and subjective factor-screening process of traditional methods like AHP with a formalized procedure, significantly enhancing objectivity and efficiency. Secondly, our proposed knowledge reasoning with relation mining method enables a dynamic evaluation of EV battery state. By adaptively computing unique parameter weights tailored to the distinct degradation characteristics of different battery chemistries (LFP, NCM, NCA), the method precisely matches each battery to the application scenario that best leverages its residual value, overcoming the limitations of traditional evaluation models. Building upon these contributions, future research should pursue two critical directions. The first is to enhance model scalability by exploring technologies such as distributed computing to efficiently handle large-scale industrial evaluation tasks. The second is to construct a multi-objective optimization model. This model would integrate our technical assessment with critical dimensions of economic viability and safety, providing quantitative decision support for complex techno-economic trade-offs. Such work will pave the way for maximizing the full lifecycle value of EV batteries and advancing the echelon utilization industry toward a more intelligent and profitable future.

CRediT authorship contribution statement

Jinhua Xiao: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Chengran Jiang:** Writing – original draft, Visualization, Investigation. **Sergio Terzi:** Writing – review & editing. **Chen Zheng:** Writing – review & editing. **Marco Macchi:** Writing – review & editing.

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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Appendix A

The main terminology and definition list.

EV	Electrical vehicle
EV	End of life
LFP	18650 lithium iron phosphate battery
NCM	Nickel-Cobalt-Manganese battery
NCA	Nickel-Cobalt-Aluminum battery
AHP	Analytic hierarchy process
PPE	Projection pursuit evaluation
EW	Entropy weight
FCE	Fuzzy comprehensive evaluation
GAT	Graph attention network
e_{ij}	The similarity coefficient between the adjacent node j and the target node i.
a	Training attention kernel
W	Weight matrix
α_{ij}	The influencing weight
h_i	The feature of the target node i
h_j	The feature of adjacent node j
d_m	A known judgement which serves as a starting point for reasoning
F_m	The result of the judgement from the pre-conditions
FPN	Fuzzy petri net
$P = \{p_1, p_2, \cdots, p_m\}$	A finite set of places
$T = \{t_1, t_2, \cdots, t_m\}$	A finite set of transitions
t_i	A transition
w_i	The value of the transition
$D = \{d_1, d_2, \cdots, d_m\}$	A finite set of preconditions
β	An associative function

Data availability

Data will be made available on request.

References

Abavi-Torghabeh, N., Kalantarian, M.M., Dehkhoda, S., Sadeghian, Z., 2023. A systematic evaluation of charge-discharge behaviors, performance, and rate-capability of Al-ion batteries. Electrochim. Acta 437, 141508. https://doi.org/10.1016/j.electacta.2022.141508.

Atalay, S., Sheikh, M., Mariani, A., Merla, Y., Bower, E., Widanage, W.D., 2020. Theory of battery ageing in a lithium-ion battery: capacity fade, nonlinear ageing and lifetime prediction. J. Power Sources 478, 229026. https://doi.org/10.1016/j.jpowsour.2020.229026.

Azadegan, A., Porobic, L., Ghazinoory, S., Samouei, P., Saman Kheirkhah, A., 2011. Fuzzy logic in manufacturing: a review of literature and a specialized application. Int. J. Prod. Econ. 132, 258–270. https://doi.org/10.1016/j.ijpe.2011.04.018.

Bai, X., Asgarpoor, S., 2004. Fuzzy-based approaches to substation reliability evaluation. Electr. Power Syst. Res. 69, 197–204. https://doi.org/10.1016/j.epsr.2003.08.011.
Baumann, M., Rohr, S., Lienkamp, M., 2018. Cloud-connected battery management for decision making on second-life of electric vehicle batteries. In: 2018 13th International Conference on Ecological Vehicles and Renewable Energies, EVER 2018. IEEE, pp. 1–6. https://doi.org/10.1109/EVER.2018.8362355.
Belt, J.R., 2010. Battery Test Manual for Plug-In Hybrid Electric Vehicles. Idaho National Laboratory.
Butylskii, D.Y., Troitskiy, V.A., Smirnova, N.V., Pismenskaya, N.D., Wang, Y., Jiang, C., Xu, T., Nikonenko, V.V., 2024. Review of recent progress on lithium recovery and recycling from primary and secondary sources with membrane-based technologies. Desalination 586. https://doi.org/10.1016/j.desal.2024.117826.
Chen, H., Zhang, T., Gao, Q., Han, Z., Jin, Y., Li, L., Yang, K., Xu, Y., Liu, X., Xu, X., Wang, S., 2022. Assessment and management of health status in full life cycle of echelon utilization for retired power lithium batteries. J. Clean. Prod. 379, 134583. https://doi.org/10.1016/j.jclepro.2022.134583.
Chen, J.F., Hsieh, H.N., Do, Q.H., 2015. Evaluating teaching performance based on fuzzy AHP and comprehensive evaluation approach. Appl. Soft Comput. J. 28, 100–108. https://doi.org/10.1016/j.asoc.2014.11.050.
Chen, L., Tong, Y., Dong, Z., 2020. Li-ion battery performance degradation modeling for the optimal design and energy management of electrified propulsion systems. Energies 13. https://doi.org/10.3390/en13071629.
Chen, X., Liu, S., Liu, R.W., Wu, H., Han, B., Zhao, J., 2022. Quantifying arctic oil spilling event risk by integrating an analytic network process and a fuzzy comprehensive evaluation model. Ocean Coast Manag. 228, 106326. https://doi.org/10.1016/j.ocecoaman.2022.106326.
Deshpande, R., Verbrugge, M., Cheng, Y.-T., Wang, J., Liu, P., 2012. Battery cycle life prediction with coupled chemical degradation and fatigue mechanics. J. Electrochem. Soc. 159, A1730–A1738. https://doi.org/10.1149/2.049210jes.
Dubois, D., Prade, H., 2015. The legacy of 50 years of fuzzy sets: a discussion. Fuzzy Sets Syst 281, 21–31. https://doi.org/10.1016/j.fss.2015.09.004.
Gao, A., Liu, B., Yue, S., 2025. The impact of channel power structures on integrated mode of recycling in a closed-loop battery supply chain. Comput. Ind. Eng. 208, 111378. https://doi.org/10.1016/j.cie.2025.111378.
Ghosh, N., Garg, A., Li, W., Gao, L., Nguyen-Thoi, T., 2021. Engineering design of battery module for EVs: comprehensive framework development based on DFT, topology optimization, machine learning, multidisciplinary design optimization and digital twins. J. Electrochem. Energy Convers. Storage 19, 1–34. https://doi.org/10.1115/1.4052042.
Guan, S., Tong, H., He, Z., Dong, Z., Gao, M., 2025. Status, challenges, and techniques of echelon utilization of retired lithium-ion batteries. J. Energy Storage 132, 117786. https://doi.org/10.1016/j.est.2025.117786.
Guo, R., Wang, F., Akbar Rhamdhani, M., Xu, Y., Shen, W., 2024. Managing the surge: a comprehensive review of the entire disposal framework for retired lithium-ion batteries from electric vehicles. J. Energy Chem. 92, 648–680. https://doi.org/10.1016/j.jechem.2024.01.055.
Hamisi, C.M., Gerutu, G.B., Greyson, K.A., Chombo, P.V., 2022. Thermal behavior of lithium-ion battery under variation of convective heat transfer coefficients, surrounding temperatures, and charging currents. J. Loss Prev. Process. Ind. 80, 104922. https://doi.org/10.1016/j.jlp.2022.104922.
Han, X., Liang, Y., Ai, Y., Li, J., 2018. Economic evaluation of a PV combined energy storage charging station based on cost estimation of second-use batteries. Energy 165, 326–339. https://doi.org/10.1016/j.energy.2018.09.022.
Jiang, W., Zhou, K.Q., Sarkheyli-Hägele, A., Zain, A.M., 2022. Modeling, reasoning, and application of fuzzy petri net model: a survey. Artificial Intelligence Review. Springer, Netherlands. https://doi.org/10.1007/s10462-022-10161-0.
Jiao, N., Evans, S., 2016. Business models for sustainability: the case of second-life electric vehicle batteries. Proced. CIRP 40, 250–255. https://doi.org/10.1016/j.procir.2016.01.114.
Kaya, İ., Çolak, M., Terzi, F., 2019. A comprehensive review of fuzzy multi criteria decision making methodologies for energy policy making. Energy Strateg. Rev. 24, 207–228. https://doi.org/10.1016/j.esr.2019.03.003.
Koc, Y., Dogru, U.E., Bilir, R.A., 2022. Evaluation of internal resistance methods for tracking battery state of health. Proc. - 2022 IEEE 4th glob. Power. Energy Commun. Conf. GPECOM 2022, 112–116. https://doi.org/10.1109/GPECOM55404.2022.9815564.
Kumar, A., Pant, S., 2023. Analytical hierarchy process for sustainable agriculture: an overview. MethodsX 10, 101954. https://doi.org/10.1016/j.mex.2022.101954.
Lai, X., Huang, Y., Deng, C., Gu, H., Han, X., Zheng, Y., Ouyang, M., 2021a. Sorting, regrouping, and echelon utilization of the large-scale retired lithium batteries: a critical review. Renew. Sustain. Energy Rev. 146, 111162. https://doi.org/10.1016/j.rser.2021.111162.
Lai, X., Huang, Y., Gu, H., Deng, C., Han, X., Feng, X., Zheng, Y., 2021b. Turning waste into wealth: a systematic review on echelon utilization and material recycling of retired lithium-ion batteries. Energy Storage Mater. 40, 96–123. https://doi.org/10.1016/j.ensm.2021.05.010.
Li, G., Xiao, X., Gui, Y., 2009. A novel algorithm of image denoising based on the grey absolute relational analysis. 2009. IEEE Int. Conf. Grey Syst. Intell. Serv. GSIS 2009, 181–185. https://doi.org/10.1109/GSIS.2009.5408327.
Li, J.X., Li, P.Z., Wang, M., Chen, C., Gao, Y., Yan, L.Y., Yang, S.C., Zhao, C., Chen, M.M., Zhang, J.S., Zhao, H.D., Li, C., Zhang, H.T., Mao, J., 2024. Study on the temperature rise characteristics of aging lithium-ion batteries under different cooling methods. Appl. Therm. Eng. 240, 122235. https://doi.org/10.1016/j.applthermaleng.2023.122235.
Li, T., Cao, J., 2017. An improved comprehensive SOC prediction method based on adaptive particle filter. In: Proceedings of the 29th Chinese Control and Decision Conference, CCDC 2017. IEEE, pp. 7023–7028. https://doi.org/10.1109/CCDC.2017.7978448.
Li, X., Wang, K., Liuz, L., Xin, J., Yang, H., Gao, C., 2011. Application of the entropy weight and TOPSIS method in safety evaluation of coal mines. In: Procedia Engineering, pp. 2085–2091. https://doi.org/10.1016/j.proeng.2011.11.2410.
Li, Z., Luo, Z., Wang, Y., Fan, G., Zhang, J., 2022. Suitability evaluation system for the shallow geothermal energy implementation in region by entropy weight method and TOPSIS method. Renew. Energy 184, 564–576. https://doi.org/10.1016/j.renene.2021.11.112.
Lih, W.C., Yen, J.H., Shieh, F.H., Liao, Y.M., 2012. Second use of retired lithium-ion battery packs from electric vehicles: technological challenges, cost analysis and optimal business model. Proc. - 2012 Int. Symp. Comput. Consum. Control. IS3C 2012, 381–384. https://doi.org/10.1109/IS3C.2012.103.
Lin, H.Y., Hsu, P.Y., Sheen, G.J., 2007. A fuzzy-based decision-making procedure for data warehouse system selection. Expert Syst. Appl. 32, 939–953. https://doi.org/10.1016/j.eswa.2006.01.031.
Liu, H., Wang, Y., Li, W., Shao, F., He, M., 2022. Decay mechanism and capacity prediction of lithium-ion batteries under low-temperature near-adiabatic condition. Inorg. Chem. Commun. 137, 109151. https://doi.org/10.1016/j.inoche.2021.109151.
Liu, H., Yang, S., Shi, G., Miao, Z., 2025. Engineering Applications of Artificial Intelligence Knowledge Graph Reasoning : Mainstream Methods , Applications and Prospects 159.
Madlener, R., Kirmas, A., 2017. Economic viability of second use electric vehicle batteries for energy storage in residential applications. Energy Proc. 105, 3806–3815. https://doi.org/10.1016/j.egypro.2017.03.890.
Moradi, M., Moradi, P., Faroughi, A., Jalili, M., 2025. Two-level attention mechanism with contrastive learning for heterogeneous graph representation learning. Expert Syst. Appl. 273, 126751. https://doi.org/10.1016/j.eswa.2025.126751.
Na, Y., Sun, X., Fan, A., Cai, S., Zheng, C., 2021. Methods for enhancing the capacity of electrode materials in low-temperature lithium-ion batteries. Chinese Chem. Lett. 32, 973–982. https://doi.org/10.1016/j.cclet.2020.09.007.
Narang, P., Kanti De, P., Peng Lim, C., Kumari, M., 2024. Optimal recycling model selection in a closed-loop supply chain for electric vehicle batteries under carbon cap-trade and reward-penalty policies using the stackelberg game. Comput. Ind. Eng. 196, 110512. https://doi.org/10.1016/j.cie.2024.110512.
Neubauer, J., Pesaran, A., 2011. The ability of battery second use strategies to impact plug-in electric vehicle prices and serve utility energy storage applications. J. Power Sources 196, 10351–10358. https://doi.org/10.1016/j.jpowsour.2011.06.053.
Oda, H., Noguchi, H., Fuse, M., 2022. Review of life cycle assessment for automobiles: a meta-analysis-based approach. Renew. Sustain. Energy Rev. 159, 112214. https://doi.org/10.1016/j.rser.2022.112214.
Podias, A., Pfrang, A., Di Persio, F., Kriston, A., Bobba, S., Mathieux, F., Messagie, M., Boon-Brett, L., 2018. Sustainability assessment of second use applications of automotive batteries: ageing of Li-ion battery cells in automotive and grid-scale applications. World Electr. Veh. J. 9. https://doi.org/10.3390/wevj9020024.
Provin, A.P., Medeiros d'Alva, A., de Aguiar Dutra, A.R., Salgueirinho Osório de Andrade Guerra, J.B., Leal Vieira Cubas, A., 2024. Closing the cycle: circular economy strategies for the textile industry using banana farming waste. J. Clean. Prod. 470. https://doi.org/10.1016/j.jclepro.2024.143352.
Rajaeifar, M.A., Ghadimi, P., Raugei, M., Wu, Y., Heidrich, O., 2022. Challenges and recent developments in supply and value chains of electric vehicle batteries: a sustainability perspective. Resour. Conserv. Recycl. 180, 106144. https://doi.org/10.1016/j.resconrec.2021.106144.
Reis, M.S., Jiang, B., 2022. Predicting the lifetime of lithium–ion batteries: integrated feature extraction and modeling through sequential unsupervised-supervised projections (USP). Chem. Eng. Sci. 252, 117510. https://doi.org/10.1016/j.ces.2022.117510.
Rohr, S., Müller, S., Baumann, M., Kerler, M., Ebert, F., Kaden, D., Lienkamp, M., 2017. Quantifying uncertainties in reusing lithium-ion batteries from electric vehicles. Procedia Manuf. 8, 603–610. https://doi.org/10.1016/j.promfg.2017.02.077.
Rossi, V., Cleeve-Edwards, N., Lundquist, L., Schenker, U., Dubois, C., Humbert, S., Jolliet, O., 2015. Life cycle assessment of end-of-life options for two biodegradable packaging materials: sound application of the European waste hierarchy. J. Clean. Prod. 86, 132–145. https://doi.org/10.1016/j.jclepro.2014.08.049.
Sáenz-Royo, C., Chiclana, F., 2025. Contribution of the ratio scale of expert judgments in the analytic hierarchy process. Expert Syst. Appl. 296. https://doi.org/10.1016/j.eswa.2025.128938.
Sanz-Gorrachategui, I., Pastor-Flores, P., Pajovic, M., Wang, Y., Orlik, P.V., Bernal-Ruiz, C., Bono-Nuez, A., Artal-Sevil, J.S., 2021. Remaining useful life estimation for LFP cells in second-life applications. IEEE Trans. Instrum. Meas. 70, 2505810. https://doi.org/10.1109/TIM.2021.3055791.
Sheng, Z., Xu, Z., Rao, H., Shao, G., 2025. Self-optimized fuzzy comprehensive evaluation for real-world webrobot detection. Appl. Soft Comput. 181, 113481. https://doi.org/10.1016/j.asoc.2025.113481.
Song, Z., Feng, S., Zhang, L., Hu, Z., Hu, X., Yao, R., 2019. Economy analysis of second-life battery in wind power systems considering battery degradation in dynamic processes: real case scenarios. Appl. Energy 251, 113411. https://doi.org/10.1016/j.apenergy.2019.113411.
Sun, L., Li, G., You, F., 2020. Combined internal resistance and state-of-charge estimation of lithium-ion battery based on extended state observer. Renew. Sustain. Energy Rev. 131, 109994. https://doi.org/10.1016/j.rser.2020.109994.
Veličković, P., Casanova, A., Liò, P., Cucurull, G., Romero, A., Bengio, Y., 2018. Graph attention networks. 6th Int. Conf. Learn. Represent. ICLR 2018 - Conf. Track Proc, pp. 1–11. https://doi.org/10.1007/978-3-031-01587-8_7.

Wu, T., Zhang, Z., Yin, T., Zhang, Y., 2022. Multi-objective optimisation for cell-level disassembly of waste power battery modules in human-machine hybrid mode. Waste Manag. 144, 513–526. https://doi.org/10.1016/j.wasman.2022.04.015.

Xiao, J., Anwer, N., Li, W., Eynard, B., Zheng, C., 2022. Dynamic Bayesian network-based disassembly sequencing optimization for electric vehicle battery. CIRP J. Manuf. Sci. Technol. 38, 824–835. https://doi.org/10.1016/j.cirpj.2022.07.010.

Xiao, J., Jiang, C., Wang, B., 2023. A review on dynamic recycling of electric vehicle battery: disassembly and echelon utilization. Batteries 9, 57. https://doi.org/10.3390/batteries9010057.

Xiao, J., Li, W., Lv, Y., Du, G., 2021. Disassembly information interoperability for electric vehicle battery in remanufacturing based on STEP standards. Proced. CIRP 104, 1873–1877. https://doi.org/10.1016/j.procir.2021.11.316.

Xu, X., Yu, F., Pedrycz, W., Du, X., 2023. Multi-source fuzzy comprehensive evaluation. Appl. Soft Comput. 135, 110042. https://doi.org/10.1016/j.asoc.2023.110042.

Yang, L., Yanhui, L., Yiyi, J., Kiyoshi, F., 2024. Forecasting the echelon utilization potential of end-of-life electric vehicle batteries: a province-level investigation in China. Clean Technol. Environ. Policy. https://doi.org/10.1007/s10098-024-03072-x.

Yin, H., Li, Y., Kang, Y., Zhang, C., 2023. A two-stage sorting method combining static and dynamic characteristics for retired lithium-ion battery echelon utilization. J. Energy Storage 64. https://doi.org/10.1016/j.est.2023.107178.

Zhang, C., Zhou, Y., Wang, X., Liu, M., Kang, C., Ci, S., 2025. A novel SOC consistency evaluation method based on dynamic reconfigurable battery energy storage system. Appl. Energy 396, 126198. https://doi.org/10.1016/j.apenergy.2025.126198.

Zhao, Haoran, Guo, S., Zhao, Huiru, 2018. Comprehensive performance assessment on various battery energy storage systems. Energies 11. https://doi.org/10.3390/en11102841.

Zhao, X., Peng, B., Zheng, C., Wan, A., 2022. Closed-loop supply chain pricing strategy for electric vehicle batteries recycling in China. Environ. Dev. Sustain. 24, 7725–7752. https://doi.org/10.1007/s10668-021-01755-9.

Zhou, K.Q., Mo, L.P., Jin, J., Zain, A.M., 2019. An equivalent generating algorithm to model fuzzy petri net for knowledge-based system. J. Intell. Manuf. 30, 1831–1842. https://doi.org/10.1007/s10845-017-1355-x.