



## Full-length article

# Dynamic Bayesian network-based disassembly sequencing optimization for electric vehicle battery



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## ABSTRACT

The sharply increasing end-of-life (EOF) battery volume in the global complex energy market has created significant challenges for its recycling and reuse, to reduce environmental pollution and resource waste, and efforts have been focused on the disassembly process considering the uncertainty of electric vehicle (EV) battery pack categories and quality. Compared with traditional disassembly, the EV battery disassembly process needs to consider more uncertainty factors for each EOF battery pack to represent its disassembly structure, which significantly reduces disassembly production efficiency. Even though sequence optimization methods for the disassembly process have been developed to solve these problems, there are still two important challenges that remain: uncertain disassembly structure representation and optimal disassembly sequence selection. To address these challenges, this paper proposes a dynamic disassembly Bayesian network approach based on an EV battery disassembly graph model. This method offers dynamic process optimization to manufacturers to deduce the optimal disassembly sequences using the forward-backward algorithm and the Viterbi decoding algorithm. To validate the proposed method, an EOF battery is used to demonstrate the disassembly sequence selection, which indicates the possibility of massive EV battery disassembly prediction.

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## Introduction

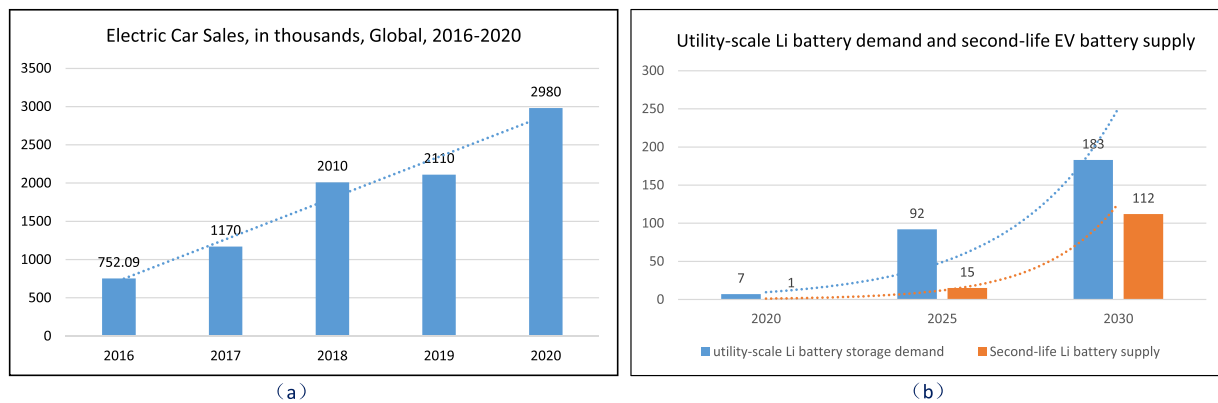
With the continuous development of the national industries and the urgent requirements of sustainable manufacturing, electric vehicle (EV) batteries have gradually formed a huge industry [1]. Although fuel vehicles are still mainstream at present, various countries have adopted policies to replace fuel vehicles under sustainable resource recycling [2]. EV batteries have also become the focus of improving energy utilization efficiency and environmental protection. EV batteries are not only used in cars, but also in other industrial fields, which largely improves the efficiency of energy utilization. Faced with the problems of battery recycling and resource recovery, various countries are gradually stipulating their regulations and policies to support sustainable battery recycling. As shown in the graphs in Fig. 1, the global battery electric vehicle sales

steadily increased from 752.09 in 2016–2980 in 2020 (in thousands) [3]. The gradually increasing trend shows the necessity of battery recycling and resource reuse for sustainable energy. According to the estimated statistics from 2020 to 2030 by McKinsey and Company, the number of utility scale Li batteries and second-life EV batteries will sharply increase in future decades [4].

The recycling of EV batteries is an urgent focus for governments and manufacturers because of its importance for the environment and other potential benefits. EV battery recycling can be regarded as a remanufacturing process called disassembly [5]. Remanufacturing, which can prolong product life and renew performance by recovering related technology, has significant effects on environmental protection [6]. Disassembly is a systematic method for separating a product into various components, subassemblies, or some parts, and is used to minimize material waste and product recycling [7]. Owing to the complexity and uncertainty of disassembly factors, it is difficult to achieve complete automation in mass production. EV battery disassembly is facing the problems of efficient battery recycling (second use and end-of-life recycling), as well as the automation of

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**Fig. 1.** (a) Global electric vehicle sales from international energy agency. (b) Estimated second-life EV battery supply and utility scale demand from 2020 to 2030 by McKinsey and Company.

massive disassembly production. Disassembly sequencing optimization is an important process that involves the optimization of EV batteries for multi-constraint and multi-objective disassembly [8]. For ecological recycling, disassembly operations are preferably used to repair damaged parts to recover their functions. It is inevitable for valuable components/subassemblies that can be recycled directly from EV battery materials, which can be used to refabricate the desired products in the green recycling process [9]. Disassembly sequences affect the disassembly process for the entire production line, and are thus obtained prior to the implementation of the disassembly process [10]. Unfortunately, many challenges still exist for the optimization of disassembly sequences due to the uncertainty of product categories and quality, which causes a change in the disassembly process for various disassembly objects and their degrees of damage, seriously affecting the disassembly production efficiency and automation levels. Most previous studies have focused on the methods of disassembly sequence optimization rather than on the dynamic disassembly process for various disassembly objects. Therefore, it is necessary to deeply explore the dynamic disassembly process for disassembly sequence optimization that is suitable for various object disassemblies.

**Literature review**

To solve the issues of the uncertainty and dynamic disassembly process for EV battery pack categories and quality, we identify the following challenges:

- Uncertain disassembly structure representation: The disassembly graph model for a specific EV battery needs to be proposed to represent disassembly relations (precedent, conflict, etc.) considering uncertainty factors.
- Optimal disassembly sequence selection: The proposed disassembly process procedure should be based on the specific disassembly graph model of an EV battery. According to the

uncertainty of disassembly objects and process parameters, dynamic disassembly sequence optimization is necessary to consider the real-time disassembly process.

However, the two scientific issues above has deep relationships between disassembly structure and disassembly sequences that support the selection of the optimal disassembly process of EV battery pack. The literature review of disassembly structure representation and disassembly optimization will be presented to compare their various application methods, and further explore the optimal disassembly method.

*Disassembly structure representation methods*

Battery recycling is commonly used to accomplish physical separation before further chemical treatment and purification steps, but it can also consider more economic and sustainable battery recovery [11]. Disassembly structures may represented by many methods (i.e., Direct graph, AND/OR graph, and Petri net) that can be used to deduce the possible disassembly roadmap as shown in Table 1.

For an uncertain disassembly structure, it is generally difficult to represent an unknown disassembly graph model that provides more detailed information of disassembly steps and states for EV battery pack. The literature review of disassembly structure representation indicates that uncertain disassembly structures need to consider more internal and external constraints and solve different disassembly objects for EV battery categories and quality.

*Disassembly sequence optimization methods*

As reviewed in many studies, various disassembly sequence optimization methods are listed, and the disassembly objects and disassembly structures are compared, as shown in Table 2. There are also many algorithms to analyze disassembly issues in this field,

**Table 1**  
Comparison with different disassembly structure representation.

Disassembly structure representation	Advantages	Disadvantages	Ref.
Direct Graph	Represent all the set of possible disassembly sequences.	Require intensive calculations for nodes and edges	Mendez et al. [12], Wartell et al. [13]
AND/OR Graph	Represent all possible disassembly tasks with AND/OR relations; Use intelligent algorithms to optimize disassembly sequence.	Difficult to integrate more task relations and modeling methods	Tian et al. [14], Edmunds et al. [15]
Petri Net	Provide more node information and modeling resources.	Disassembly information is too complex and it's difficult to simultaneously represent multiple disassembly object.	Kumar et al. [16], Kuo et al. [17]

**Table 2**  
Comparing representative research works on disassembly sequence issues.

Ref.	Disassembly sequence optimization methods					Disassembly objects		Disassembly structure
	ACO	ANN	GA	MD	Others	Single	Multiple	
Xu et al. [18]					✓	✓		Known
Gunji et al. [19]	✓		✓			✓		Known
Alshibli et al. [20]			✓			✓		Known
Tian et al. [21]		✓	✓			✓		Known
Tang et al. [22]					✓	✓		Uncertain
Mehmet et al. [23]			✓			✓		Known
Rickli et al. [24]			✓			✓		Uncertain
Feng et al. [25]					✓		✓	Known
Alfaro-Algaba et al. [26]					✓	✓		Known
Schafer et al. [27]					✓	✓		Known
Huang et al. [28]		✓				✓		Known
Lu et al. [29]	✓			✓			✓	Known
Laili et al. [30]					✓	✓		Uncertain
Hula et al. [31]			✓	✓			✓	Known
Han et al. [32]					✓		✓	Known
Cheng et al. [33]					✓	✓		Known
Tseng et al. [34]	✓					✓		Known

ACO, ant colony optimization; ANN, artifact neural network; GA, genetic algorithm; MD, making decisions; disassembly object, single/multiple; disassembly structure, uncertain/known.

such as genetic algorithms (GA), improved ant colony algorithm (ACA), adaptive particle swarm optimization (PSO) methods, and artifact neural networks (ANN).

Most researchers have focused on finding the optimal disassembly sequence based on various algorithms, neglecting actual constraint conditions for different product categories and quality. Disassembly sequence optimization is still an important issue in the disassembly process based on uncertainties and complex structures. However, these studies lacked dynamic optimization methods to solve real-time disassembly sequencing generations. This literature review presents two main research problems.

1. How can we develop a dynamic disassembly structure representation approach for EV batteries that can continuously generate disassembly graph structures for various battery categories and quality?
2. How can we implement such a disassembly sequencing optimization and infer the optimal disassembly sequence of the EV battery pack and acquire the optimization results?
3. Dynamic disassembly Bayesian network approach

In order to find out the optimal disassembly sequences in EV battery pack, the method of disassembly optimization needs to be proposed to dynamically solve the disassembly structure and disassembly sequences when facing with various uncertain situations. For conducting EV battery disassembly on a large-scale, it is necessary to present a universal disassembly sequence optimization approach to incorporate the uncertainty of battery categories and quality. To consider each dynamic step of the disassembly sequence for the EV battery, a dynamic Bayesian network (DBN) model can be proposed as follows:

- To describe the constraint conditions for a feasible disassembly sequence. Based on the disassembly sequence AND/OR graph model for a specific EV battery, the related constraints are presented and described more intuitively.
- Build a DBN model according to a specific disassembly sequence. The DBN-based disassembly method should not only represent the specific disassembly process completely, but also reduce the difficulty of subsequent inference prediction. To support the DBN and hidden Markov model (HMM) in dealing with the model inference and parameter learning of a specific EV battery disassembly sequence, which is used to acquire the optimization result.

The methods of EV battery disassembly sequence based on DBM/HMM can result in the optimal disassembly sequence in the actual production process as shown in Fig. 2.

### Disassembly graph model

A disassembly sequence for a specific product is necessary to provide a feasible method to conduct disassembly operations in an actual production line. A disassembly AND/OR graph is represented by  $G = (V, E)$ , where  $V = (v_1, v_2, \dots, v_N)$  is the set of nodes, where each element has a one-to-one correspondence with a component/sub-assembly of a product.  $N$  is the number of elements in  $V$  (i.e., the number of subassemblies/components of a product).  $E = \{e_{ij}\}$  is the set of directed edges,  $e_{ij}$  is a directed edge in an AND/OR graph, and represents a disassembly operation from node  $v_i$  to node  $v_j$ . As shown in Fig. 3, the disassembly AND/OR graph of an EV battery pack represents all the disassembly sequences. In the disassembly graph, each letter (i. e. :A, B, C, D, E, F, G, H, I, J) in each node represents a component/subassembly, respectively, where all components/subassemblies are indicated by integers in parentheses (i. e. : (1), (2), ..., (N)), and a specific number (i. e. : 1, 2, ..., M) defines a specific disassembly operation. The precedence matrix  $P = [p_{jk}]$  is used to represent the precedence relationship among the disassembly operations in an AND/OR graph model. Here,  $j$  and  $k$  are the indexes of the operation.

$$p_{jk} = \begin{cases} 1, & \text{if operation } j \text{ can be performed} \\ & \text{before operation } k \\ 0, & \text{Otherwise} \end{cases} \quad (1)$$

The conflict matrix  $C = [c_{jk}]$  is used to represent the conflict relationship between operations in the disassembly sequencing graph model, which specifies the “OR” relationship in a disassembly process, where one of two operations can occur. Here,  $j$  and  $k$  are the indexes of the operation.

$$c_{jk} = \begin{cases} -1, & \text{if operation } j \text{ and } k \text{ conflict} \\ & \text{with each other} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

The incidence matrix  $G = [g_{ij}]$  is used to represent the relationship between components/subassemblies and operations in the disassembly sequence graph model. Here  $i$  represents the index of a subassembly, and  $j$  represents the index of operation.

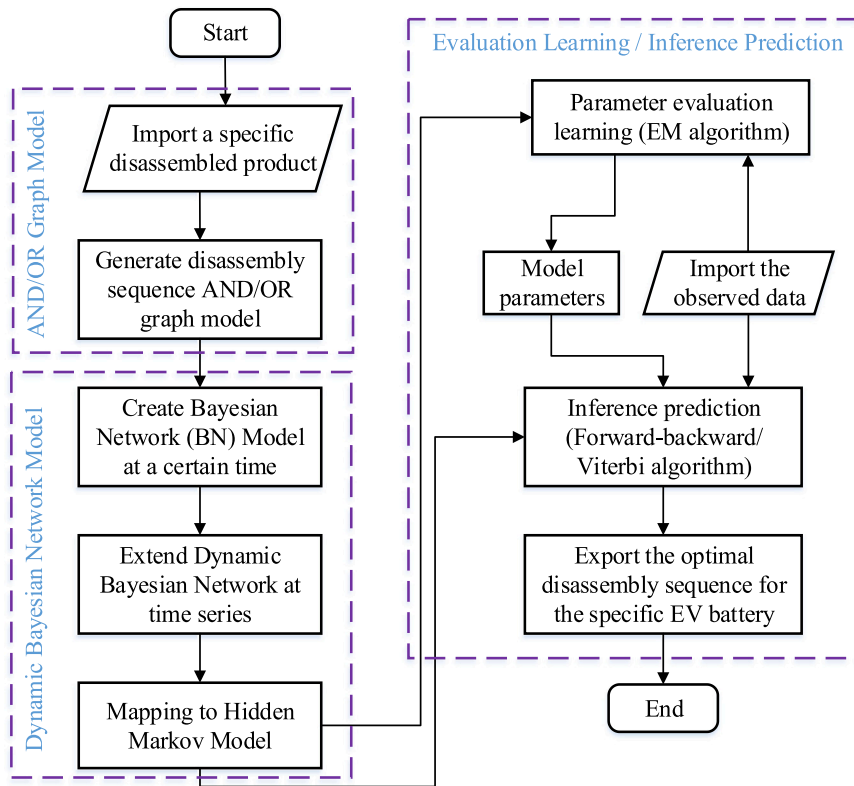


Fig. 2. Flow chart of DBN-based disassembly sequence optimization.

$$g_{ij} = \begin{cases} 1, & \text{if subassembly } i \text{ is obtained by operation } j \\ -1, & \text{if subassembly } i \text{ is disassembled by operation } j \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

For a given disassembly process, a feasible disassembly sequence should satisfy the following constraints:

$$\sum_{j=1}^J x_j \geq 1 \quad (4)$$

$$x_k = \sum_{j=1}^J y_{jk}, k = 1, 2, \dots, J \quad (5)$$

$$p_{jk} - y_{jk} \geq 0, j, k = 1, 2, \dots, J \quad (6)$$

$$0 \leq \sum_{j=1}^J g_{ij} x_j \leq 1, i = 1, 2, \dots, N \quad (7)$$

$$\sum_{j=1}^J y_{jm} \geq \sum_{k=1}^J y_{mk}, m = 1, 2, \dots, J \quad (8)$$

$$\sum_{m=1}^J y_{jm} \leq 1, j = 1, 2, \dots, J \quad (9)$$

$$x_j, y_{kj} \in \{0, 1\}, j, k = 1, 2, \dots, J \quad (10)$$

Here,  $i$  represents the index of a component/subassembly,  $i \in \{1, 2, \dots, N\}$ , where  $N$  is the number of all nodes in a given graph model.  $j, k, m$  represents the index of an operation,  $j, k, m \in \{1, 2, \dots, J\}$ , where  $J$  represents the number of operations.  $x_j$  denotes that if operation  $j$  is performed,  $x_j = 1$ ; otherwise,  $x_j = 0$ .  $y_{jk}$  denotes that if operation  $k$  is performed after operation  $j$  is performed,  $y_{jk} = 1$ ; otherwise,  $y_{jk} = 0$ . Moreover, Eq. (4) ensures that at least one operation is performed during the disassembly process (not including the initial operation). Eq. (5) guarantees that each operation can be performed at most once. Eq. (6) guarantees the feasibility between operations, that is, the disassembly sequence satisfies the precedence matrix. Eq. (7) guarantees the relationship between a component/subassembly and an operation: (1) a component/subassembly cannot be disassembled if it has not been previously obtained; (2) multiple operations cannot disassemble a component/subassembly at the same time. Eq. (8) ensures a balance between the input and output of components/subassembly, and there is an operation  $m$  that prevents the disassembly sequence at this step. Eq. (9) guarantees that components/subassembly can be disassembled by at most one operation. Eq. (10) guarantees that the variables  $x_j, y_{kj}$  can only be 0 or 1.

#### Dynamic Bayesian network approach

The random variable set of a BN model can be presented as  $X$ , and its extended variables in the DBN model can be written as  $X[1], X[2], \dots, X[t]$  with time factors at various state moments  $t$ . We extended the BN model at multiple discrete moments and combined it with a time series to build the DBN model. The conditional probability is assumed to be stable and consistent for time series.

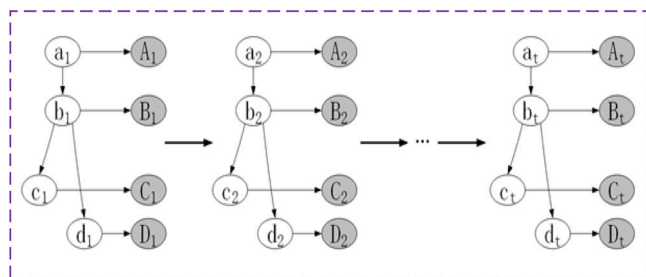


Fig. 3. Dynamic Bayesian network with the hidden nodes and the observed nodes with various time series.

The dynamic disassembly process is conducted with a set of time series, and the dynamic probabilistic process is Markovian, that is,

$$P(X[t + 1]|X[1], X[2], \dots, X[t]) = P(X[t + 1]|X[t]) \tag{11}$$

In other words, the probability depends only on the present moment and not on the past. The conditional probability process at the adjacent time was stable;  $P(X[t + 1]|X[t])$  is independent of time  $t$  and the transition probability  $P(X[t + 1]|X[t])$  at different times can be obtained easily.

Therefore, we can expand the more reasonable BN model based on the discrete timeline, and obtain the DBN model for various time series, as shown in Fig. 3;  $a_t, b_t, c_t, d_t$  represent the moment  $t$  of the hidden nodes  $a, b, c, d$  based on the specific disassembly sequence graph model, respectively.  $A_t, B_t, C_t, D_t$  represent the moment  $t$  of the observed nodes  $A, B, C, D$  for the graph model, respectively.

### DBN-based inference prediction

The purpose of DBN-based inference and learning prediction is to solve the probabilistic calculation for a given DBN structure and to calculate system model parameters and structures consistently. To reasonably present and better understand the model parameters, some symbols need to be listed;  $x_t$ : the hidden variable at time  $t, x_t \in \{1, 2, \dots, n\}$ ;  $y_t$ : the observation variable at time  $t, y_t \in \{C1, C2, \dots, Cm\}$ ;  $i, j$ : the index of the state of the hidden variable,  $i, j \in \{1, 2, \dots, n\}$ ;  $k$ : the index of the state of the observation variable,  $k \in \{C1, C2, \dots, Cm\}$ . There are three main model parameters for the HMM.

- 1) Initial hidden state distribution matrix:  $\Pi = (\pi_i)_{1 \times n}$ , where  $\pi_i = P(x_1 = i)$ .
- 2) Hidden state transition matrix:  $A = (a_{ij})_{n \times n}$ , where  $a_{ij} = P(x_{t+1} = j | x_t = i)$ .
- 3) Observation matrix:  $B = [b_i(k)]_{n \times m}$ , where  $b_i(k) = P(y_t = k | x_t = i)$ . However, the parameters of the HMM can be simplified as  $\lambda = (A, B, \Pi)$ .

Considering the model parameter  $\lambda$  and the observation sequence  $Y$ , the observation sequence  $Y$  is the set of all observed node states from time 1 to  $T$ , and  $Y = \{y_1, y_2, \dots, y_T\}$ . If the observation sequence  $Y$  is known, then all the observation node states are known. The probability of occurrence of the observation sequence is depicted as  $P(Y|\lambda)$ . Further,  $\alpha_t(i)$  is calculated recursively using the forward algorithm, and then  $\beta_t(i)$  is calculated recursively by the backward algorithm. The forward-backward algorithm is as follows:

1. To define the forward variable:  $\alpha_t(i) = P(y_1, y_2, \dots, y_t, x_t = i | \lambda)$ ;  
 Initialization:  $\alpha_1(i) = \pi_i b_i(y_1), 1 \leq i \leq n$   
 Recursion:  $\alpha_{t+1}(j) = [\sum_{i=1}^n \alpha_t(i) a_{ij}] b_j(y_{t+1})$   
 Result:  $P(Y_T | \lambda) = \sum_{i=1}^n \alpha_T(i)$
2. To define the backward variable:  $\beta_t(i) = P(y_{t+1}, y_{t+2}, \dots, y_T | x_t = i, \lambda)$ ;  
 Initialization:  $\beta_T(i) = 1, 1 \leq i \leq n$ .  
 Recursive:  $\beta_t(i) = \sum_{j=1}^n a_{ij} b_j(y_{t+1}) \beta_{t+1}(j); 1 \leq i \leq n, t = T - 1, \dots, 1$ .  
 Result:  $P(Y_T | \lambda) = \sum_{i=1}^n \pi_i \beta_1(i)$ .  
 Therefore, the forward-backward algorithm is obtained:

$$P(Y_T | \lambda) = \sum_{i=1}^n \alpha_t(i) \beta_t(i), 1 \leq t \leq T \tag{12}$$

Based on the model parameter  $\lambda$  and the observation sequence  $Y$ , we can find the most likely hidden sequence  $X$ . The hidden sequence  $X$  is the set of all hidden node states from time 1 to  $T, X = \{x_1, x_2, \dots, x_T\}$ . The Viterbi decoding algorithm is as follows:

- 1) Define the Viterbi variable:  $\delta_t(i) = \max_{x_1, x_2, \dots, x_{t-1}} P(x_1, x_2, \dots, x_{t-1}, x_t = i, Y_t | \lambda)$ ,  $\psi_t(i)$  is the optimal hidden sequence at the moment  $t - 1$ ;

- 2) Initialization:  $\delta_1(i) = \pi_i b_i(y_1), i = 1, 2, \dots, n$

$$\psi_1(i) = 0, i = 1, 2, \dots, n$$

- 3) Recursion: For  $t = 1, 2, \dots, T$

$$\delta_t(i) = \max_{1 \leq j \leq n} [\delta_{t-1}(j) a_{ji}] b_i(y_t), i = 1, 2, \dots, n$$

$$\psi_t(i) = \operatorname{argmax}_{1 \leq j \leq n} [\delta_{t-1}(j) a_{ji}], i = 1, 2, \dots, n$$

- 4) Calculation:  $P = \max_{1 \leq i \leq n} \delta_T(i)$

$$\hat{X}_T = \operatorname{argmax}_{1 \leq i \leq n} [\delta_T(i)]$$

$$\text{For } t = T - 1, T - 2, \dots, 1$$

$$\hat{X}_t = \psi_{t+1}(\hat{X}_{t+1})$$

- 5) Find the optimal hidden sequence  $X_T = \{\hat{X}_1, \hat{X}_2, \dots, \hat{X}_T\}$ .

If the observation sequence  $Y$  is known and the parameter  $\lambda$  of the HMM model is unknown, we can find the maximum probability of observation sequence  $P(Y|\lambda)$  with the optimal parameter  $\lambda$ . The classical expectation maximization (EM) algorithm was used to acquire the optimal parameters of the HMM model. If the hidden sequence  $X$  can be observed, the learning process of the HMM is very simple. The hidden variables define  $x_1, x_2, \dots, x_T$ . The algorithm replaces the actual value with the expected statistic value and estimates its probability  $P(X|Y)$  in the inference process. The EM algorithm is briefly described through the following steps.

- 1) Expectation process with an initial model parameter  $\lambda$ .

$$E[N(i, j) | \lambda^k] = E[\sum_{t=2}^T I(x_{t-1} = i, x_t = j) | Y_T] \\ = \sum_{t=2}^T P(x_{t-1} = i, x_t = j | Y_T) = \sum_{t=2}^T \xi_{t-1,t|T}(i, j)$$

where  $i, j$  are indices of the hidden node state.  $k$  is the number of iterations.  $\lambda^k$  is the model parameter after  $k$  iterations.  $I(x)$  is a binary function that is 1 when  $x$  is present and 0 when  $x$  is not present.  $N(i, j) = \sum_{t=2}^T I(x_{t-1} = i, x_t = j)$  is the number of transitions from state  $i$  to state  $j$  with a given length  $T$ .  $\xi$  can be calculated using the forward-backward algorithm,  $\xi_{t-1,t|T}(i, j) = \frac{\alpha_t(i) a_{ij} b_j(y_{t+1}) \beta_t(j)}{P(Y|\lambda)}$ ,  $E[N(i, j) | \lambda^k]$  is called the expected sufficient statistic (ESS).

- 2) Maximizing the Max Likelihood Estimation (MLE) value for given data.  $\lambda^{k+1} = \operatorname{argmax}_{\lambda} Q(\lambda | \lambda^k)$ , where  $Q$  is an auxiliary function  $Q(\lambda | \lambda^k) = E[P(Y_T, X_T | \lambda) | \lambda^k]$ .

### Case study

Based on the above method of dynamic Bayesian network model for EV battery disassembly, a case study is proposed to verify the performance of the disassembly optimization method that can be used to analyze the possibility of disassembly sequence when facing with complex uncertain EV battery situations. A common lithium iron phosphate battery pack is utilized for the case study as shown in Fig. 4, including {A}- pole head cover, {B}- upper end cover, -pole head, {D}- module circuit board, {E}- pole piece, {F}- structure frame, {G}- battery module/cell, {H}- thick

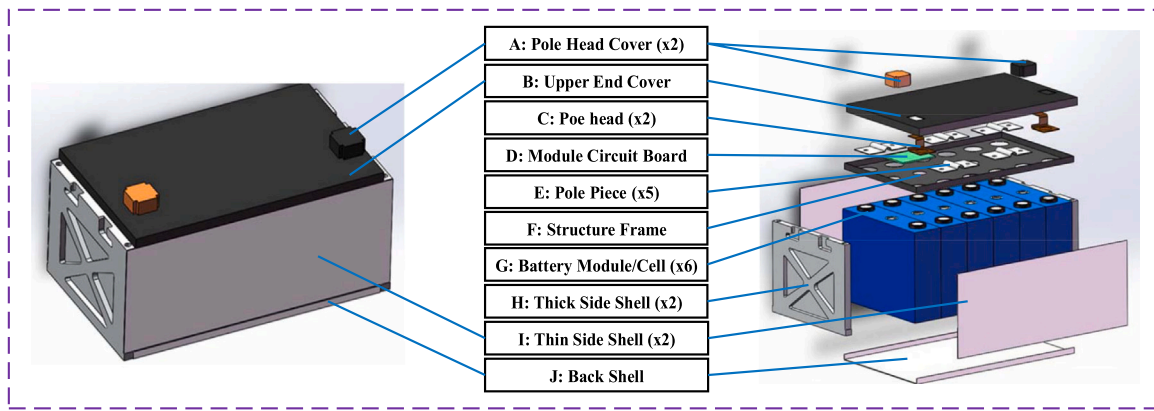


Fig. 4. Overview of 3D model of EV battery pack and its associated components.

side shell, {I}- thin side shell, and {J}- back shell. Therefore, the following constraints for disassembly are proposed for the disassembly sequence of the EV battery pack: (1) {B} must be disassembled after {A}; (2) {D}, and {E} must be disassembled after {B}; (3) {F} must be disassembled after {D} and {E} are all disassembled; (4) {G} must be disassembled after {D}, {E}, and either {F} or {G} can be disassembled.

Each combination of adjacent edges is numbered, which represents a disassembly step to generate two or more components/subassemblies in a disassembly operation, as shown in Fig. 5. Related constraints can represent the equilibrium relationship between the in-degree and out-degree of operations. For instance, subassembly {(2)} is a parent of subassembly {(4)} and subassembly {(6)}, subassembly {(4)} is a child of subassembly (1).

As shown in Fig. 5, through operation 1, subassembly {(1)} is disassembled into subassemblies {(2)} and {(16)}. Using Operation 3, subassembly {(2)} can be disassembled into subassembly {(4)} and {(17)}. To illustrate, the precedence matrix describes the precedence relationship for parent and child subassembly or components that it might lead to different disassembly operations. The precedence matrix of the disassembly sequence for a specific EV battery can be calculated as shown in Fig. 6.

The same parent subassembly or component can be disassembled by different disassembly operations that generate different child subassemblies or components. For example, the parent {(1)} can be disassembled to obtain subassembly {(2)} and {(16)} through operation 1, or {(3)} and {(14)} through operation 2, but only one of them can be executed for a feasible disassembly sequence. To clarify, the conflict matrix describes the conflict relationships for specific operations during the disassembly process based on different decisions. The conflict matrix of the disassembly sequence for a specific EV battery can be calculated as shown in Fig. 7.

The incidence matrix of the disassembly sequence for the EV battery shown in Fig. 5 is shown in Fig. 8.

To deeply explore the dynamic disassembly process for EV batteries, we simplify the disassembly graph model, as shown in Fig. 9(a), to analyze the optimization of disassembly sequences. Considering the mapping from the disassembly sequence graph model to the DBN model, we need to connect different nodes related to the graph model to obtain the hidden nodes in the BN model. Then, each hidden node in the BN model corresponds to an observed node. The hidden node refers to the specific components/subassemblies of the actual disassembly sequence, and the observed node refers to each observed component/subassembly, as shown in Fig. 9(b).

Owing to the simple disassembly structure of EV batteries, the dynamic BN graph model is suitable for battery disassembly sequence optimization. To demonstrate the optimization procedure of

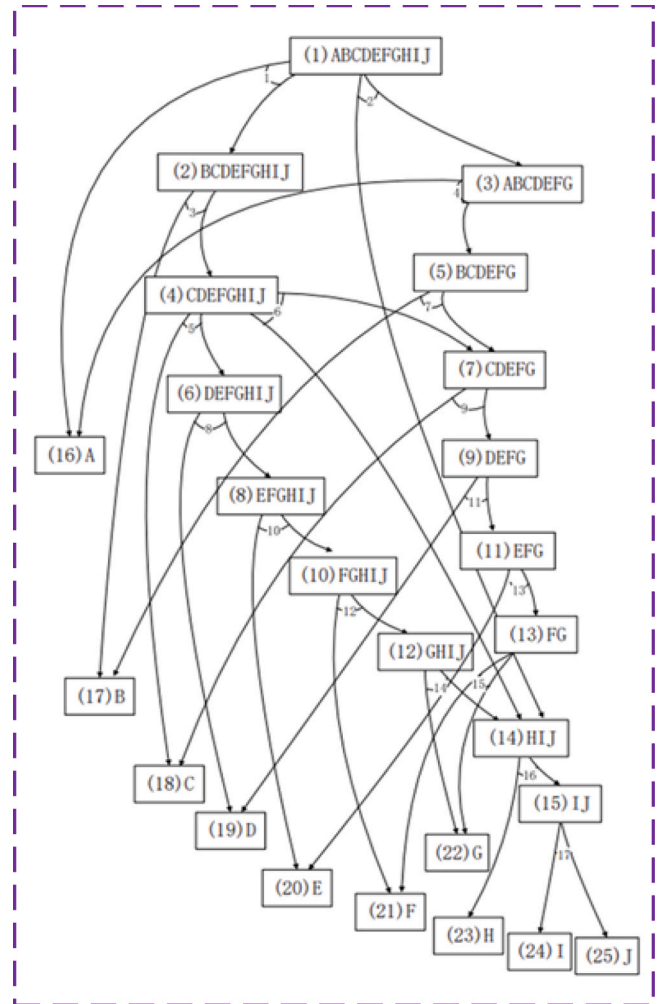


Fig. 5. Disassembly AND/OR graph model of certain EV battery.

the EV battery disassembly sequence, we simplify the issue regarding the number of nodes in the BN model. As shown in Fig. 9, the original hidden node a of the disassembly sequence refers to subassembly {(2)} in the graph model. The second hidden node b is linked to the set of components/subassemblies {(17); (4)} in the disassembly sequence graph model. The third hidden node c is linked to the set of components/subassemblies {(18);(6)} in the graph model. The fourth hidden node d is linked to the set of components/subassemblies {(7);(14)} in the graph model. Observed



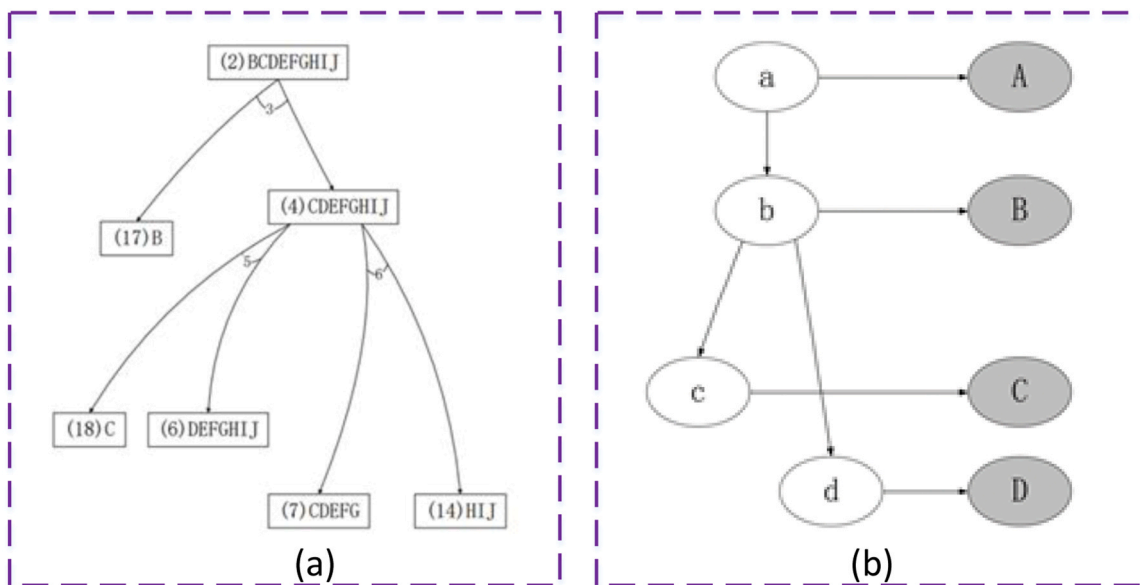


Fig. 9. (a) Partial disassembly sequence graph model for certain EV battery. (b) The BN model related to disassembly operation (Gray is observation node).

Table 3  
The different states of the hidden nodes in HMM.

Hidden node	a	b	c	d
$x_t$				
1	0	0	0	0
2	0	0	0	1
3	0	0	1	1
4	0	0	1	0
5	0	1	0	0
6	0	1	0	1
7	0	1	1	1
8	0	1	1	0
9	1	0	0	0
10	1	0	0	1
11	1	0	1	1
12	1	0	1	0
13	1	1	0	0
14	1	1	0	1
15	1	1	1	1
16	1	1	1	0

Table 4  
The different states of the observation nodes in DBM.

Observed node	A	B	C	D
$y_t$				
C1	0	0	0	0
C2	0	0	0	1
C3	0	0	1	1
C4	0	0	1	0
C5	0	1	0	0
C6	0	1	0	1
C7	0	1	1	1
C8	0	1	1	0
C9	1	0	0	0
C10	1	0	0	1
C11	1	0	1	1
C12	1	0	1	0
C13	1	1	0	0
C14	1	1	0	1
C15	1	1	1	1
C16	1	1	1	0

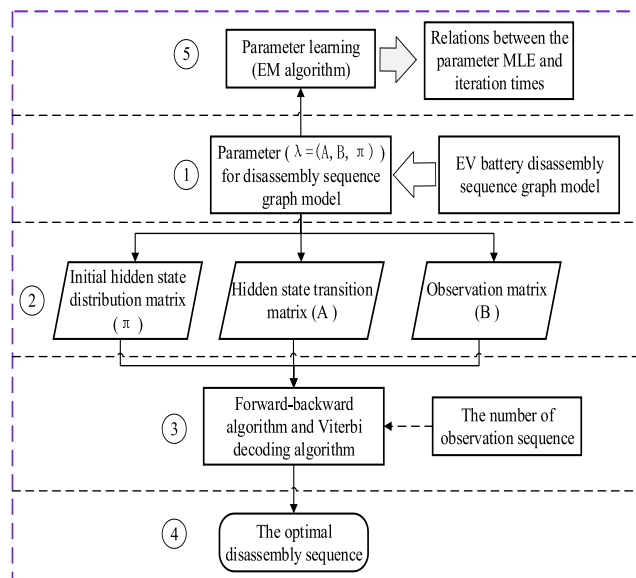


Fig. 10. Procedure of disassembly sequence optimization analysis for EV battery.

$$\Pi = (\pi_t)_{1 \times 16} = [0.1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0.9 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]$$

Fig. 11. Initial hidden state distribution matrix  $\Pi$  in the actual disassembly.

probability for all disassembly operations, we define the parameters of the hidden state transition matrix A:

- (a) Any subassembly has an 80% probability of disassembly, and a 20% probability of no disassembly that is, the state at the last moment remains unchanged). It is necessary to define the probability that the subassembly will not be disassembled. However, in the actual disassembly process, disassembly may need to be stopped in the human-machine collaboration

$$A = (a_{ij})_{16 \times 16} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.4 & 0 & 0.4 & 0.2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 12. Hidden state transition matrix A in actual disassembly process at the same probability of disassembly operations.

- disassembly process to ensure that the subsequent disassembly can be performed better and more safely.
- (b) If the subassembly can be disassembled by different operations, the disassembly probability of each operation is the same. For example, if the subassembly {(4)} can be disassembled by either Operation 5 or Operation 6, the probability of Operations 5 and 6 is considered to be the same at 40%.
  - (c) Some components/subassemblies need not be further disassembled, such as subassemblies {(6)}, subassemblies {(7)}, and subassemblies {(14)}.

The hidden state transition matrix A at the same probability of disassembly operations is shown in Fig. 12.

According to the actual disassembly process at different probabilities of disassembly operations, we define the parameters of the hidden state transition matrix A :

- (a) Any subassembly has an 80% probability of disassembly and 20% probability of not disassembly.
- (b) If components/subassemblies can be disassembled by different operations, the probabilities of each operation are different. For example, the subassembly {(4)} can be disassembled by either Operation 5 or Operation 6, and the probability is not the same. We consider that the probability of Operation 6 to be slightly higher than that of Operation 5.
- (c) Some components/subassemblies need not be further disassembled, such as subassemblies {(6)}, subassemblies {(7)}, and subassemblies {(14)}.

The hidden state transition matrix A at different probabilities of the disassembly operations is shown in Fig. 13.

In addition, this can artificially generate probabilistic differences for a biased parameter that verifies the optimal disassembly sequence using the Viterbi decoding algorithm and HMM inference.

$$A = (a_{ij})_{16 \times 16} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.3 & 0 & 0.5 & 0.2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 13. Hidden state transition matrix A in actual disassembly process at the different probability of disassembly operations.

The hidden state transition matrix  $A = (a_{ij})_{n \times n}$  describes the row vectors. If state  $i$  exists, the sum of the row vectors is 1. If state  $i$  does not exist, the sum of the row vectors is zero. We need to consider the dynamic disassembly process for the next time whether it is disassembled into another state or not to maintain the original state, namely for state  $i$  of its probability  $\sum_{j=1}^{16} P(x_{t+1} = j | x_t = i) = 1$ .

- 3) The observation matrix  $B = (b_i(k))_{n \times m}$  describes the HMM model variables for the state and observation nodes to the probability of state  $k$ , namely  $b_i(k) = P(y_t = k | x_t = i)$ . It refers to the probability of a certain observed node state in the actual disassembly process. For example, the observation results of subassembly {(6)} and a subassembly {(18)} in the disassembly sequence only account for 50%, 25%, and 25%, respectively, and the probability of the remaining observations is 0. We know that  $b_4(C4) = 0.5$ ,  $b_4(C1) = 0.25 + 0.25 = 0.5$ , and other  $b_4(k) = 0$ . However, observation matrix B involves the hidden node and observation node, including 16 states for both. To understand the disassembly graph model more intuitively, the hidden node refers to the collection of multiple components/subassemblies by the disassembly operation. When the hidden node is 1, it means that all the components/subassemblies refer to the hidden and observed nodes, and the observation node is also 1. When the number of hidden nodes is zero, the component/subassembly does not exist or is not complete. Therefore, the observation node may be either 0 or 1. For example, when the hidden node is 1 ( $b = 1$ ), there are components {(17)} and subassembly {(4)} at the node position. The probability of the observed node was 100% and  $b = 1$ . When the hidden node is 0 ( $b = 0$ ), it means that there may be no component or only component {(17)} at the node position, and then the observation might not be correct. We know that a 75% probability makes  $b = 0\%$ , and 25% probability makes  $b = 1$ . For the hidden node a, it refers to only component {(2)}, and its observed node must be correctly mapped to the hidden node. The hidden nodes c and d refer to the component/components that will continue to be disassembled (see Fig. 7). However, if the hidden node is 1 ( $b = 1$ ) for the hidden variable state  $i$  in the HMM model, the observed variable state  $k$  at the same time must be simultaneously linked to state  $i$ , for example,  $b_5(C5) = P(y_t = C5 | x_t = 5) = 1$ . If the hidden node is 0 ( $b = 0$ ) for the hidden variable state in the HMM model, the observed variable state  $k$  has a probability of 75% linking to state  $i$  or a probability of 25% linking to another state. For example,  $b_1(C1) = P(y_t = C1 | x_t = 1) = 0.75$ ,  $b_1(C5) = P(y_t = C5 | x_t = 1) = 0.25$ .

Observation matrix B is shown in Fig. 14. Namely, if state  $i$  of the observation matrix exists, the sum for each row vector is 1. If state  $i$  of the observation matrix does not exist, the sum for each row vector is zero. Therefore, we can determine the probability of state  $i$ , namely,  $\sum_{k=C1}^{C16} P(y_t = k | x_t = i) = 1$ .

$$B = (b_i(k))_{16 \times 16} = \begin{bmatrix} 0.75 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.75 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.75 & 0 & 0 & 0 & 0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Fig. 14. Observation matrix in the HMM for EV battery disassembly process.

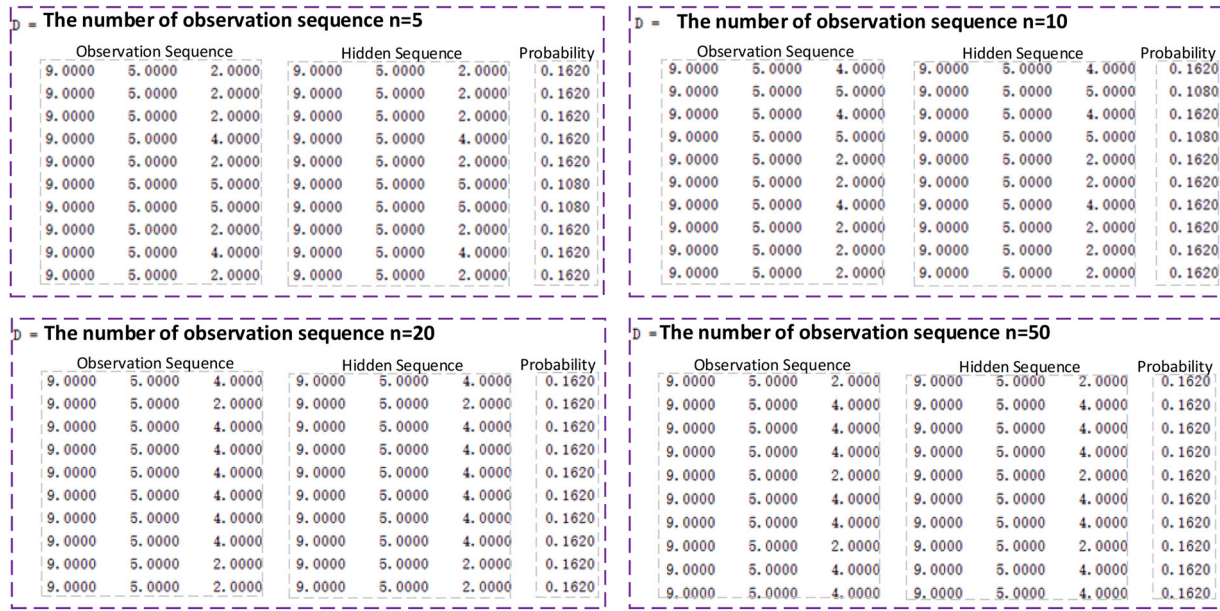


Fig. 15. The observation sequence, hidden sequence, and the biggest probability of observation sequence at different number of observation sequence (n = 5, 10, 20, 50) for EV battery disassembly sequence.

Furthermore, the forward-backward algorithm is used to acquire the parameters of the HMM model that calculates the probability of the observation sequence, while the Viterbi algorithm is used not only for the observation sequence, but also for the hidden sequence linked to the observation values. The purpose of disassembly sequence inference is to verify whether the optimal disassembly sequence can be obtained from a large number of observation sequences, where we choose the one with the highest probability. Normally, the observation sequence is randomly and casually generated by inference algorithms with related model parameters to deduce the optimal results. In fact, the analysis of disassembly sequence inference involves iterating the possible observation sequence and then choosing the optimal observation value. It is important to ensure that the number of observation sequences is suitable. We set up the model parameters, including the transformation matrix, observation matrix, original hidden state, length of observation sequence, and hidden sequence. In other words, we compared the different numbers of observation sequences for n = 5, 10, 20, and 50, and the results are shown in Fig. 15.

By comparing the above four matrices D for the observation and hidden sequence, we infer that the number of observation sequences will influence the disassembly sequence for a specific EV battery. When the number is small, it may be difficult to find the optimal disassembly sequence based on the probability of the observation sequence. With the increasing number of observation sequences, the possibility of a disassembly sequence will be reduced. Therefore, when the number of observation sequences is large, the probability of finding the optimal disassembly sequence may be higher. However, if the number of observation sequences reaches a certain value, the number of observation sequences will affect the accuracy of the optimal result. Therefore, we need to calculate a suitable number of observation sequences to ensure the optimal disassembly sequence without mistakes and calculation waste. However, we noticed that when the number (n = 50) of the observation sequences is 50, the probability of obtaining the optimal disassembly sequence might be higher in the HMM. Therefore, we can obtain the optimal disassembly sequence for 9 → 5 → 4 and 9 → 5 → 2 (see Table 1). However, in the actual disassembly process, there is no possibility that the same probability of disassembly operation is executed to obtain an optimal disassembly sequence, and we need to

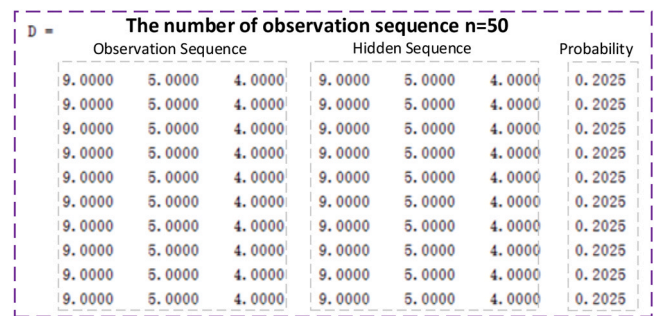


Fig. 16. The observation sequence, hidden sequence, and the biggest probability of observation sequence at n = 50 for the different probability of each disassembly operation.

consider the different probabilities of disassembly operations to guarantee the actual optimal disassembly sequence, as shown in Fig. 16.

Typically, the hidden state transition matrix A at the different probabilities of each disassembly operation is defined as the model parameters to acquire the optimal disassembly sequence 9 → 5 → 4 (see Table 1) with a higher probability than 9 → 5 → 2 (see Table 1), as shown in Fig. 15. We know that the inference of the disassembly sequence can accurately acquire the optimal disassembly sequence. Based on the inference of the disassembly sequence, we define the total length of the disassembly sequence (T = 3) at different probabilities of disassembly operation for the number of observation sequences. The optimal disassembly sequence in the graph model (as shown in Fig. 7) is 9 → 5 → 4 (see Table 1 and Table 2), which means that 9 can translate into a {1, 0, 0} sequence to execute the hidden node a for the first step, namely the subassembly {(2)}. Furthermore, 5 can also be translated into {0, 1, 0, 0} to execute the hidden node b from the second step, where subassembly {(2)} is disassembled into subassembly {(18)} and subassembly {(6)} through operation 3. Then, 4 can be translated into {0, 0, 1, 1} to execute the hidden node c from the third step, where subassembly {(6)} is disassembled into subassembly {(7)} and subassembly {(14)} through operation 6. The optimal disassembly sequence is illustrated in Fig. 17.

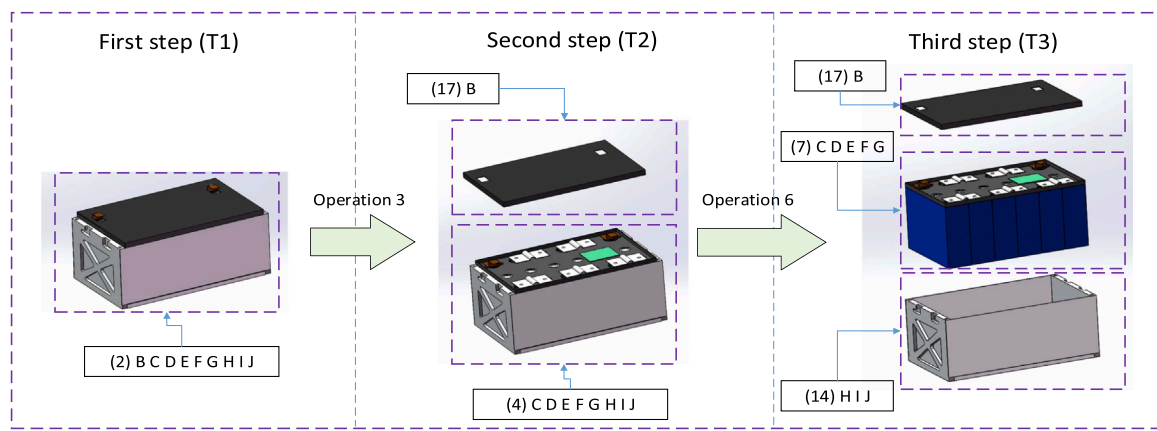


Fig. 17. An optimal disassembly sequence for EV battery.

**Discussion**

Considering the challenges of the implementation of the disassembly process for EV batteries in actual production, the authors presented a novel dynamic disassembly Bayesian network approach to optimize disassembly sequences. The proposed method has the following advantages:

- First, regarding the solution to the uncertainty of disassembly object categories and quality in the massive disassembly production process, the proposed disassembly approach provides manufacturers with a means to dynamically optimize the disassembly sequence in the EV battery disassembly process. This means that manufacturers can rapidly ensure disassembly structures for certain disassembly objects based on the disassembly graph model.
- Second, the authors proposed a dynamic Bayesian network model approach in which the EV battery disassembly sequence can be obtained by inferring the probability of disassembly steps with various time series. In this disassembly approach, the sequence optimization selection is not only completed by general algorithms, but also by a dynamic Bayesian network approach to help manufacturers solve the uncertainty of disassembly objects in the large-scale disassembly production process.

However, although the authors' research team has successfully applied the proposed disassembly approach in EV battery disassembly cases, several perspectives for future research based on this approach are still recommended.

- The continuously growing pressure of EV battery recycling volume in complex markets demands the development of new strategies to deal with battery disassembly with acceptable and affordable costs. In this challenging context, the rapid and efficient acquisition of the optimal disassembly sequence has been explored by different authors. However, disassembly constraints and related parameters need to be given according to the actual disassembly objects and their quality. The authors' study demonstrates that it is possible to utilize knowledge-based engineering (KBE) to solve these problems [35]. KBE can be used to represent disassembly knowledge [36] and automate disassembly task decision making [37]. It can better provide the reusability of previous disassembly knowledge. By combining the dynamic disassembly Bayesian network approach, KBE might support the possibility of disassembly system optimization and decision-making. Therefore, in order to accomplish the disassembly process for EV batteries, there are many aspects that require further study.

- With the increasing volume of end-of-life (EOF) products, under the proposal of green production, efficient and energy-saving recycling is being considered with second or multiple reuse. For example, EOF batteries are being studied to realize the echelon utilization of waste power batteries [38], which can efficiently utilize health battery modules or cells. Therefore, EV battery recycling through disassembly may involve some further constraints with complex battery health detection. It is very difficult to fully generalize the disassembly structure for EOF batteries, and these constraints and relations need to be considered comprehensively.
- The disassembly peculiarity of EV battery is more being attracted than other product disassembly from battery pack to battery cells, including the specific types of disassembly joints, the consequent electric hazard, the availability of safety plugin, etc. These peculiar disassembly features has important influences on determining the optimal disassembly sequence that is difficult to ensure the specific situations of each battery with the uncertainty from the recycling markets. However, it is necessary to consider the disassembly operation peculiarities of EV battery that can be used to support the efficient disassembly production and the effective decision-making tools [39]. Therefore, the peculiarities of battery disassembly are very meaningful to explore its internal relationships and possible influences in the actual disassembly production line.

**Conclusions**

To solve the issue of the optimization of EV battery disassembly sequence when faced with the uncertainty of battery categories and quality, a dynamic disassembly Bayesian network approach is proposed in this paper. The main contributions of this study lie in the following two aspects. The constraints in the feasible disassembly process have been developed using the disassembly sequence graph model, which can be used to describe the disassembly relations (i.e., precedence, conflict, and incidence) for the disassembly sequence. Therefore, based on a dynamic Bayesian network (DBN) to accomplish the EV battery disassembly sequences, we proposed a novel method to transform the disassembly sequence graph model into the DBN model. For disassembly sequence prediction, the hidden Markov model (HMM) is proposed to complete the inference and learning of model parameters using the forward-backward algorithm and the Viterbi decoding algorithm for disassembly sequence prediction. The optimal disassembly sequence for a specific EV battery was realized by demonstrating the disassembly procedure of an EV battery during the actual disassembly process.

## 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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