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Exploring the Performance Impact of Neural Network Optimization on Energy Analysis of Biosensor

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Abstract

With the popularization of new energy vehicles, lithium battery systems, as the main components of new energy vehicles, have the characteristics of short life cycles and harmful substances inside. The green treatment of lithium battery systems has become a research hotspot. Disassembly and recycling are essential means of reusing waste in lithium battery systems. Due to the wide variety of lithium battery systems, the lack of unified design standards, and the high flexibility requirements for disassembly, manual disassembly is currently the primary method used. However, this method can cause health hazards to oneself when dismantling some harmful components. The optimization of the dismantling process route for lithium

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batteries is a crucial step before dismantling, which directly determines the economic benefits of dismantling. However, unlike general electromechanical products, lithium batteries have prominent safety issues during the dismantling process, so the safety requirements for their dismantling process route are relatively high. Given the substantial absence of parametric evaluation and modification in prior research, this work investigates the influence of the most significant factors on the power density of biosensors. A conduction-based framework was employed to ascertain these variables, and the calculations were performed utilizing a neural network. The neural network was developed with Particle Swarm Optimization (PSO). Based on this, this article considers studying the optimization method of the lithium battery safety disassembly process to maximize safety and economic benefits comprehensively. Based on the essential characteristics of lithium-ion battery systems, an analysis is conducted on the allocation method of difficulty level for human-machine cooperation tasks and the impact indicators of task allocation. Then, a product disassembly hybrid diagram is established, and on this basis, multiple sets of human-machine cooperation disassembly sequences are generated. Finally, a multi-objective optimization model for disassembly cost, difficulty, and time is established. Finally, taking the Tesla Model 1sPBS waste lithium battery as an example, the safety prediction model for dismantling the waste lithium battery and the optimization model for the safety dismantling process route were solved to verify the effectiveness of the above optimization method.

Keywords:

Used lithium batteries, dismantling safety, neural networks, multi-objective optimization, biosensors.

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Introduction

Biosensors have undergone extensive development and are currently experiencing continuous expansion, with numerous uses in the ecological, food, and biomedical sectors (Haleem et al., 2021). Optimizing materials for electrodes and detecting parameters is crucial for enhancing sensor effectiveness. Most research often optimizes a single variable at a time, which is uncomplicated yet challenging, mainly when multiple elements interact. The parameters established for the preparation and operation of the sensor do not represent the genuine optimum, hindering the effective deployment of electrochemical detectors in the field or point-of-care diagnosis (Naresh & Lee, 2021). An experimental development, a chemometric instrument, has been developed for the methodical and statistically trustworthy improvement of parameters. Electrochemists need more time to employ this beneficial technique for fabricating and optimizing their biosensors.

With the joint development of society, science, and technology, the manufacturing industry is developing rapidly, and the speed of updating and replacing new energy products is accelerating, resulting in many waste products (Nawafleh & Al-Oqla 2024). The rare metals inside discarded new energy products have great economic recovery value, such as cobalt, lithium, nickel, manganese, and other metals stored inside discarded lithium battery systems, have high economic recovery value (Shou et al., 2024). At the same time, harmful substances in discarded lithium battery systems of biosensors can cause environmental pollution. The recycling and treatment of discarded products face many challenges. In recent years, with the increasingly severe problems caused by global warming, reducing carbon emissions has become a significant challenge that must be solved for sustainable social development (Karthick & Gomathi 2024; Ji, 2024). Promoting transforming energy structure from fossil fuels to green new energy is integral to solving this problem. Developing new energy vehicles, especially electric vehicles, is a microcosm of this transformation in China. Since 2009, China has been promoting the development of new energy-electric vehicles (Nawafleh & Al-Oqla, 2024). After 2014, electric vehicles have entered a period of rapid development, as shown in Figure 1. In 2020, the annual sales of electric vehicles in China exceeded 1.35 million, a year-on-year increase of 11%. It is estimated that the cumulative number of new energy vehicles in China has reached 4.9 million, and more than 1.5 million new electric vehicles will be added annually.

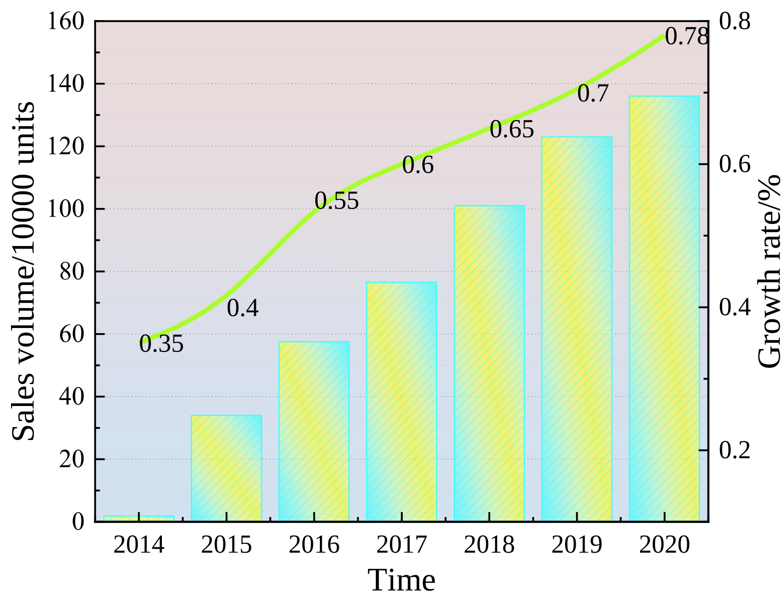

Figure 1. Sales trend of electric vehicles in china

Waste lithium batteries can be disassembled to obtain individual battery cells, which can be reused after restructuring and consistency testing (Shou et al., 2024). In some situations with low battery capacity, such as low-speed electric vehicles, energy storage systems, etc., cells or modules identified as unqualified during the disassembly process will be resourced. As the core management device for lithium-ion battery energy storage of biosensors, BMS highly integrates functions and management, estimates battery status through real-time monitoring of various parameters, and achieves comprehensive, efficient, and refined management of batteries in order to extend battery life, improving battery safety and utilization, and other purposes (Zhang et al., 2024; Meng et al., 2024; Ewees et al., 2024; Sikirica et al., 2024). SOC and SOH are key state variables for BMS evaluation management, and their accuracy directly affects the safety and effectiveness of the BMS system. Therefore, accurate estimation of SOC and SOH can improve the effective management of lithium batteries of biosensors, enhancing electric vehicles' endurance and driving safety.

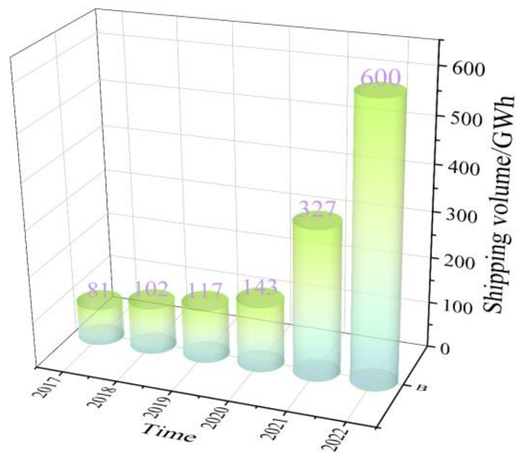

Figure 2. Trend of china's power lithium-ion battery shipment volume

From Figure 2, it can be intuitively seen that from 2017 to 2020, the annual growth rate of lithium battery shipments remained between 15GWh and 25GWh (Wu et al., 2024). However, since 2021, the shipment volume of lithium batteries has proliferated, almost doubling every year. In 2022, the shipment volume has reached 600 GWh. The shipment volume of lithium batteries in China is expected to exceed 1000 GWh in 2023, reaching another new height.

In these optimization investigations, the Genetic Approach (GA) was employed. Other gradient-free techniques, such as Particle Swarm Optimization (PSO), can save computation time and enhance optimization procedures. Metaheuristic approaches such as Neural Networks (NN) and Artificial Intelligence (AI) were developed (Wang & Zhang, 2024). A review study has examined the uses of artificial neural networks in renewable energy. A further research paper examines the application of PSO in renewable energy networks of biosensors and contrasts PSO with other algorithms to handle challenges in this domain (Ma et al., 2024; Mohan et al., 2024; Tan et al., 2024; Carine Menezes Rebello et al., 2024). The research utilized a PSO technique to identify proton transfer membrane fuel cell parameters and analyze voltage-current information. The suggested model has been verified using both empirical and simulated data.

PSO regulates maximum power point tracking in windmills. A real-time improvement has been included to decrease the runtime using neural networks. This work presents a rapid and accurate real-time optimizing method applicable to diverse types and topologies of renewable sources. AI and NN are progressively utilized throughout all scientific, technical, and cultural disciplines.

Basic Theory of Safe Disassembly Process Route for Lithium Batteries

System Structure of Lithium Batteries

PBS mainly includes a Battery Management System (BMS), necessary power electronic equipment, and modules formed by battery cells. The battery module and battery system of biosensors are both equipped with a cooling system (Asif et al., 2024; Kazi & Mahdi, 2024; Helal et al., 2024). The BMS is placed outside the insulation shell and connected to power electronic equipment. Due to the heavy handling of battery modules, automated disassembly by robots can effectively reduce time and avoid damage to the waist caused by workers during the handling process. The connection methods of the battery cells and conductive connectors inside the battery module are divided into three types: welding, screw connection, and mechanical compression connection. The following is an explanation of three connection methods:

1. Welding: Currently, battery modules of biosensors are divided into laser welding, ultrasonic welding, and resistance welding (Jiang et al., 2024). A bayonet structure fixes multiple lithium battery cells on a plastic plate, and then a battery pack is generated by laser welding. As welding stabilizes the electrode onto the cylindrical battery, destructive disassembly is required during the disassembly process.
2. Screw connection: The battery cells of biosensors are fixed with screws, and battery systems with larger individual capacities are fixed with screw connections (Guo et al., 2024).
3. Mechanical crimping: Through an elastic slit structure, the electrodes on the battery are clamped onto the conductive components of the module, and a stable current is obtained. The mechanical crimping connection method is easy to disassemble while saving the welding process and obtaining a complete battery cell (Soman & Sarath, 2024).

Structural adhesive or double-sided tape is usually used between the battery cells and the battery cell, as well as between the battery cells and the module casing, to integrate the battery cells and the module and meet the requirements of stable operation after vibration impact and drop (Soman & Sarath, 2024). Table 1 shows the battery bonding materials. Due to the use of structural adhesive for bonding materials, violent disassembly is required during the disassembly process. Currently, using robots for disassembly can avoid the low efficiency of manual disassembly and avoid damage to the waist.

Table 1. Battery bonding materials

Types of	Bonded structure	Adhesive material	Notes
Square shell battery	The battery cells are bonded and positioned, and the side panels and end panels are bonded and fixed	Two component polyurethane	Due to the weight of the square shell battery body, there is expansion between the cells, so a high-strength adhesive is used for buffering. The module can transfer heat after bonding using high-strength adhesive and a specific thermal conductivity. The cylindrical battery cell requires adhesive while also having performance indicators such as thermal conductivity.
Soft pack battery	Positioning of battery cells and aluminum shells using adhesive bonding	FB49	
Cylindrical battery pack	Adhesive bonding between battery cells and bases	Propylene structural adhesive	

Wires connect the battery units in the lithium battery module of biosensors. Fiberboards separate the battery modules, and a fuse connects each battery in the modules (Meng et al., 2024). The battery module is connected to the I/O main line and connected in parallel to the contactor at the output end. Based on the above summary and analysis, the general structure of lithium batteries is summarized, and the general components of Table 2 PBS are obtained.

Table 2. PBS general components

Number	Name
1	PBS upper cover
2	Battery Management System (BMS)
3	Insulated wire head
4	Battery Module
5	MAIN FUSE
6	Coolant pipeline
7	Unit Control Module (CMC)
8	I/O Mainline

Lithium Battery Disassembly Process Flow

The dismantling process of waste lithium batteries of biosensors can be divided into battery pack dismantling, module dismantling, and single-cell dismantling according to the hierarchy of dismantling objects, as shown in Figure 3.

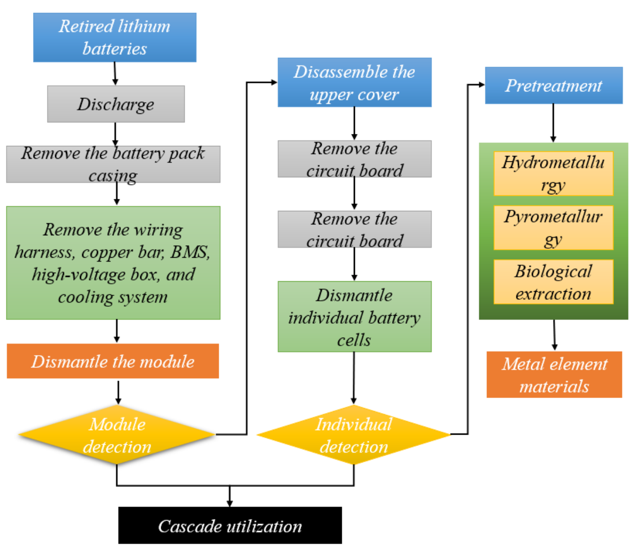

Figure 3. Process flow for dismantling lithium batteries

- Disassemble the battery pack. At present, retired lithium batteries are usually recycled per pack, including multiple modules and their interconnecting components. The task of dismantling used lithium battery packs is to remove the constraints between the two and remove the most valuable modules (Cheng et al., 2024). At the beginning of disassembly, due to the uncertainty of the battery pack's battery capacity of biosensors, it is necessary first to undergo discharge treatment to reduce the battery capacity as much as possible. Then, components such as wire harnesses, copper bars, BMS, etc., are dismantled sequentially to obtain multiple modules.

- Module disassembly. After disassembling the modules from the battery pack of biosensors, it is necessary to inspect each module to evaluate whether it can be reused at the module level (Liu, et al., 2024). If so, the disassembly process is completed. Otherwise, the modules will be further disassembled. Modules are usually composed of stacked or parallel battery cells。

- Disassemble individual battery cells. Similarly, the individual battery cells of biosensors removed from the module must be tested to determine whether they can be reused (Katırcı et al., 2024). If so, the disassembly is complete. If not, it is considered that their reuse value is low and cannot be fully utilized while ensuring their complete structure. Therefore, resource utilization methods can only be used to recover their precious metal elements.

Framework for Lithium Battery Disassembly Planning

During the dismantling process of PBS, the battery must first be tested for discharge to ensure that humans or robots are not harmed during the dismantling process. The battery system has two cooling methods. If it is air-cooled, the air-cooled machine should be disassembled (Jin et al., 2024). Remove the connection components and bolts from the battery system, and then remove the upper housing and high-voltage main upper housing. Then, the battery harness and fuse of the electronic control system are disassembled, and the battery management system (BMS) is dismantled. After completing the above disassembly, the battery module will be disassembled. The disassembled module PCB board, battery cells, and other parts will be processed as resources, as shown in the following figure, the planning box for the PBS disassembly process (Wang et al., 2024).

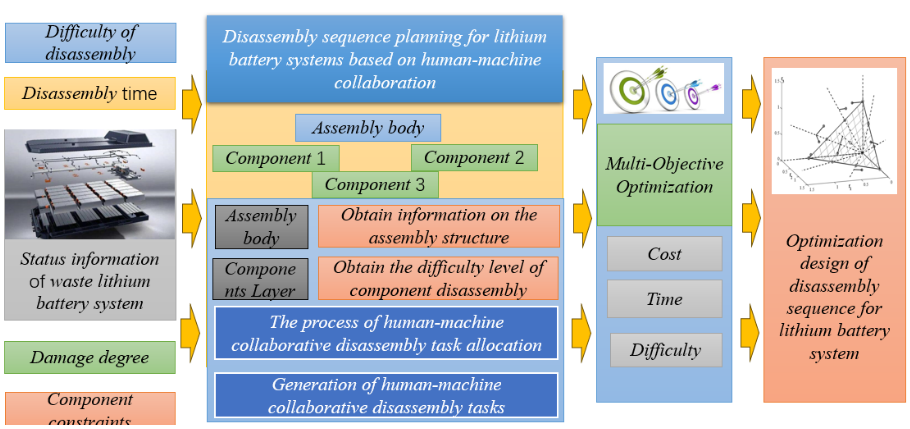

Figure 4. PBS disassembly process planning framework

- Information acquisition. Obtain information on the constraints, degree of damage, primary current status, and disassembly time of internal components in PBS, and then analyze the factors affecting the disassembly difficulty of each element to obtain information on the disassembly status of PBS.
- A disassembly sequence planning method based on human-machine cooperation (Wang et al., 2024). Analyze the task allocation method for human-machine collaboration, combine human-machine collaboration with PBS characteristics, establish a hybrid diagram and task allocation method for human-machine collaborative disassembly of parts, and generate multiple sets of human-machine collaborative disassembly sequences.
- Multi-objective optimization of disassembly sequence (Cui et al., 2024). Taking dismantling cost, dismantling time, and dismantling difficulty as dismantling objectives, an improved firefly algorithm was used to optimize the model and obtain the optimal dismantling sequence for PBS.

Analysis of Safety Characteristics Factors for Dismantling Waste Lithium Batteries

Due to the uncertainty of the service environment, critical information, such as the degree of failure of internal connectors and the state of battery cells in lithium batteries of biosensors, are still being determined during recycling. Different dismantling and recycling enterprises have different dismantling and recycling capabilities, which makes the characteristic factors affecting the safety of dismantling waste lithium batteries diverse (Wu et al., 2024). Therefore, this article summarizes the distinguishing factors that affect the safety of dismantling waste lithium batteries from internal and external perspectives, including their storage capacity of biosensors, degree of failure, and dismantling tools, to ensure the effectiveness and comprehensiveness of their prediction results.

Internal Characteristic Factors

The internal characteristic factors that affect the safety of biosensors' used lithium batteries are the characteristics that affect the safety of dismantling due to performance changes in their internal components during long-term service, including the storage capacity and failure characteristics of used lithium batteries.

The Relationship between the Storage Capacity of Waste Lithium Batteries and their Disassembly Safety: The capacity of lithium batteries decreases continuously with the increase in service time. After the capacity decreases from 70% to 80%, its capacity will experience a cliff-like decay. Lithium batteries of biosensors are unsuitable for continued service in electric vehicles and should be considered for disassembly and recycling. Therefore, for lithium battery dismantling and recycling companies, the capacity of used lithium batteries still accounts for more than 70% of new batteries, and they generally have a certain amount of stored electricity, usually exceeding 350V. In this high voltage situation, the consequences of electric shock for dismantling technicians are dire, and it will increase the damage to equipment caused by short circuits during the dismantling process. Therefore, discharge operations are generally carried out before dismantling used lithium batteries of biosensors, reducing storage capacity (Shen et al., 2024). The commonly used discharge methods currently include resistance-based consumption methods and equipment recycling methods. The former uses resistance-based energy-consuming components to consume the stored electricity of waste lithium batteries. At the same time, the latter connects waste lithium batteries to energy storage systems and transfers the stored electricity.

The Relationship between the Failure Characteristics of Waste Lithium Batteries and their Disassembly Safety: After years of service, the internal components of lithium batteries will experience varying degrees of failure, including electrode material damage, electrolyte deterioration, and structural component corrosion. When the electrode material of a lithium battery of biosensors is damaged, dendrites will grow locally in the battery cell. If the dendrites are too long, they penetrate the separator, causing an internal short circuit. During the dismantling process of waste lithium batteries, external pressures such as dismantling tools or personnel operations can increase the probability of internal short circuits, generating a large amount of heat during the dismantling process and causing dangerous accidents such as heating and self-initiation. Under normal circumstances, lithium batteries inevitably undergo reactions to produce gases, especially toxic hydrogen fluoride gas that reacts with water and accumulates in a closed space, causing battery swelling. When the operator disassembles during the dismantling process, the release of toxic gases can pose a threat to its safety.

External Characteristic Factors

The external characteristic factors that affect the safety of dismantling waste lithium batteries refer to the characteristic factors that affect the dismantling safety of waste lithium batteries during the dismantling process due to the limitations of the enterprise's dismantling ability, including dismantling tools, dismantling methods, and dismantling environment.

The connection between the dismantling tools for used lithium batteries and their dismantling safety: In the case of known high voltage of discarded lithium batteries of biosensors, when using the dismantling tools in the table to disassemble their corresponding connection methods, it is necessary to avoid increasing the probability of dangerous accidents such as spontaneous combustion or large-scale gas leakage caused by high voltage, which is mainly reflected in limiting the conductivity and heat generation thermal conductivity of the dismantling tools. Because most dismantling tools for used lithium batteries of biosensors are metal products, such as screwdrivers, wrenches, etc., which have strong conductivity, using these dismantling tools under high voltage conditions can increase the possibility of damage to the safety of dismantling personnel and the stable operation of dismantling equipment. Therefore, when dismantling used lithium batteries of biosensors, it is advisable to choose dismantling tools with insulation materials such as rubber that can cover the parts humans can touch and reduce the probability of electric shock. The heat generation and dissipation performance of dismantling tools can also affect the safety of dismantling waste lithium batteries. Due to the need for sealing and fixing, most waste lithium battery modules are connected by welding. If tools such as grinding wheel cutting machines are used for disassembly, high temperatures of over 900 degrees Celsius will be generated due to severe friction between the grinding wheel and aluminum alloy shells during disassembly. Generally, the ignition point of the electrolyte in waste lithium battery cell materials is the lowest, only about 130 degrees Celsius, and the positive electrode material will ignite at 200 degrees Celsius; therefore, using a grinding wheel cutting machine for disassembly will significantly increase the probability of battery self-ignition and have low safety. If it wants to minimize the likelihood of hazardous accidents caused by the heat generated by disassembly tools during the disassembly process, it can choose disassembly tools such as hot air guns with controllable heat production performance or set up cooling and cooling devices to improve the heat dissipation ability of disassembly tools.

The connection between the dismantling method of waste lithium batteries and their dismantling safety: Due to the different service environments of lithium batteries, waste lithium batteries with varying connection methods also have different degrees of failure. In this case, choosing the corresponding disassembly method and selecting disassembly tools are necessary. Due to the relatively concentrated high-voltage components inside discarded lithium batteries, it is essential to consider the disassembly position and direction when disassembling parts related to these components. For example, when disassembling waste lithium battery modules, the disassembly should start from the end facing away from high voltage, and the module should be opened in a direction parallel to the electrode material to avoid short circuit accidents caused by vertical cutting damaging the cell structure. During the dismantling process of waste lithium batteries, the number and amplitude of their movements should be minimized to the greatest extent possible, including rotation, flipping, and other operations, to reduce the probability of dangerous accidents such as liquid leakage or release of toxic gases caused by connection failure caused by external pressure coupled with failed internal components of the battery. Finally, for the severely failed parts in waste lithium batteries, the non-destructive disassembly method that maximizes the preservation of the complete structure makes it challenging to achieve the disassembly task. However, destructive disassembly methods such as cutting and crushing can cause irreversible structural damage to waste lithium batteries of biosensors, and the damage to the sealing structure can also increase the probability of accidents such as electrolyte leakage or harmful gases during the disassembly process. Therefore, in the dismantling process of waste lithium batteries, choosing a dismantling position and direction far away from the high-voltage source is necessary, as well as minimizing the number and amplitude of battery movement during the dismantling process. At the same time, non-destructive dismantling methods should be adopted to reduce the adverse impact of dismantling methods on the safety of waste lithium battery dismantling.

Optimization Design and Application of Firefly Algorithm Neural Network

Backpropagation (BP) Neural Network Model

Artificial neural networks emulate the natural brain's response system, which involves the reception of external stimuli using dendritic ports and creating neural interactions and related responses among neurons and nerve fibers to form a network framework. Neurons interpret and combine signals, constructing a neural network system through a layer-by-layer dissemination procedure. This framework can be represented as a topological framework comprising an input level, hidden layers, and an output level, each containing multiple cells, as illustrated in the subsequent figure of the neural network topology system.

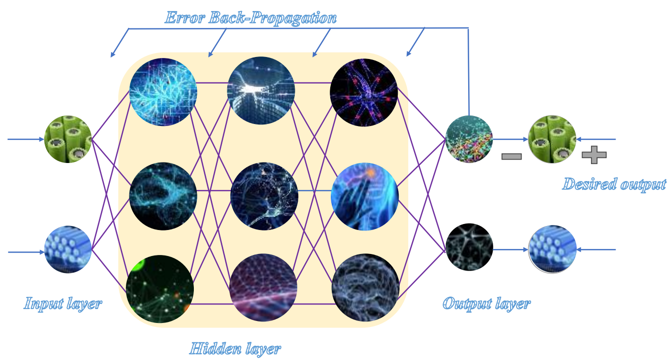

Figure 5. Neural network proton model

A Back Propagation (BP) neural network is a model of an error forward propagation neural network. The modification and assignment of threshold weights are sent from the output layer to the input level, whereas mistakes spread reversely. The main task of the BP neural network is to perform parameter linear regression and complicated model categorization. The essential aspect of training a BP neural network model is the modification of the weights for each layer and the thresholds of the hidden or output layers. This threshold signifies the minimum limit of error propagation, which influences the speed and precision of the overall neural network model performance. The weights denote the adjustments each neuron must make during error transmission. Theoretical foundations dictate that errors are backpropagated from the concealed levels to assign mistakes to each neuron. The gradient descent method is employed to identify the optimal configuration, iteratively training the model until the discrepancy between the computed actual value and anticipated value is reduced.

Test of Fitting Function for Battery Pack Shell Parameters Using New Firefly Optimization Algorithm

This article found the power core of new energy-pure electric vehicles - the battery pack and its outer shell entity. From a practical base near a new energy vehicle processing factory, electronic three-level high-precision scales were used to weigh the solid weight of the battery pack's outer shell and entire body and packaged as a whole. Vernier calibrators and other dimensional measuring instruments were employed to ascertain the external measurements of the newly developed battery pack's exterior shell and to do a three-dimensional analysis; the overall weight of the pack's battery is 236.19 grams. In the modeling process, each size parameter functions as an input for the design variables. At the same time, mass (M), first-order modal frequencies (F), pressure (F1), and stress displacing (S) are designated as the output goals. T1 (mm) denotes the thickness of the bottom shell of the battery housing; T2 (mm) indicates the width of the rear side panels; T3 (mm) signifies the covering width; L1~L4 (mm) signifies the width of the ears (1-4), etc. The precise range of size characteristics is presented in Table 3:

Table 3. Range of design variable values

Parameter	Value range
Thickness of bottom plate of lower shell T1 (mm)	1-5
Rear panel thickness T2 (mm)	1-5
Upper shell thickness T3 (mm)	7-9
Thickness of the sidewall of the front suspension ear T4 (mm)	3-5
Thickness of transverse bars on the upper shell T5 (mm)	2-5
Upper shell front extension plate T6 (mm)	1-5
Thickness of lifting ears (1-4) L1-L4 (mm)	7-9
Thickness of the side wall of the rear suspension ear L5 (mm)	7-9
Thickness of grooves around the upper shell L6 (mm)	1-2

By natural selection and the survival of the fittest, animals have developed different frameworks and optimum survival and predation strategies to adapt to various surroundings. Studies invented a biomimetic algorithm, the Firefly Optimization Search Algorithm, which utilizes female fireflies to respond to the unique flashing patterns of male fireflies by mimicking their unique flashing characteristics, sensitivity to light intensity, and mutual attraction. The algorithm includes information such as communication, mating, and warning. This algorithm is based on the firefly's pursuit of brighter companions in search patterns, and from these search patterns, the optimal search pattern suitable for modern engineering has been found and modified. The optimal search algorithm used in this article is an optimization algorithm that improves and optimizes the traditional firefly algorithm. It is a new algorithm based on firefly search and locating brighter companions.

Improving the Firefly Algorithm Optimization Process

From the initial firefly optimization algorithm, the algorithm has two fatal flaws. Firstly, when a firefly individual with weaker luminescence moves to search for one with stronger luminescence, the current brightest firefly individual does not update its position in real-time until a new brightest firefly appears. In other words, when other fireflies with weaker brightness move to search for the current brightest firefly, Some individuals need to cross a long distance to match, which increases the difficulty of searching and moving. Conversely, suppose the brightest firefly can move in real-time according to the position of different fireflies with weaker light. In that case, it will significantly reduce the calculation time and search for the optimal speed. Secondly, for fireflies with weaker luminescence, when the firefly with the most robust brightness moves its position, its individual cannot quickly locate new unknowns and move, which can also lead to an increase in computation time and even the possibility of convergence failure. Therefore, in response to the above two issues, this article uses the improved Firefly algorithm to optimize the structure of new energy battery shells and construct a new neural network prediction model using the Firefly algorithm. The position update process of the improved Firefly algorithm is shown in Formula 1:

$$X_t^{t+1} = X_j^t + \beta_{i,j}^t\left(X_j^t - X_i^t\right) + \alpha \cdot \varepsilon \quad (1)$$

In the formula, Xjt+1 represents the t+1st position of the bright firefly, α, The step size factor represents the iterative calculation, and ϵ Represents random vectors.

Through the above calculation, real-time updates of individual positions of bright fireflies can be achieved, changing the drawbacks of traditional firefly algorithms and achieving further improvement. After updating the position, the firefly population will perform iterative calculations for the selection and position transformation of individuals with light, solid fireflies. The firefly swarm must continually update its location to maintain the best output parameter. In light of the newly derived design parameter and goal function standards, the initial optimal location is supplanted by the newly identified optimal location. The iterative computation persists until the ideal solution is identified. Iteration has concluded; please provide the final computation result.

Analysis of Disassembly Sequence Instances

Overview

Due to its outdated design and long service life, the scrapping volume of Tesla Model 1s PBS is also showing explosive growth. Therefore, this article takes Model 1 PBS as the research object of biosensors. The power system of Model 1sPBS includes 11 battery modules, a battery management system (BMS), and necessary power electronic equipment. By collecting and analyzing the information, the disassembly time, difficulty, and information of Model 1s PBS were obtained, as shown in Table 4.

Table 4. Model 1sPBS disassembly information

number	Component Name	Manual disassembly time (s)	Automatic disassembly time（s）	Disassembly direction	remover	Difficulty of manual disassembly	Autostrip difficulty
1	case	180	90	+z	Hand/Pliers	0.75	0.25
2	Upper shell screw	51	29	+z	screwdriver	0.25	0
3	Soundproof cotton	45	27	+z	Hand/Pliers	0	0.25
4	High pressure assembly upper housing	30	24	+z	Hand/Pliers	0	0
5	High pressure assembly upper housing screws	45	27	+z	screwdriver	0.25	0
6	fuse	24	15	+z	Hand/Pliers	0.25	0.25
7	Battery pack film	60	36	/	Hand/Pliers	0	0
8	generatrix	45	23	/	Hand/Pliers	0.25	0
9	Metal Separator	42	30	+z	Hand/Pliers	0.25	0.5
10	Fiberboard	15	9	/	Hand/Pliers	0	0
11	Insulation pad	27	18	/	Hand/Pliers	0.25	0.75

Algorithm Effectiveness Verification and Performance Analysis

To verify the effectiveness and superiority of the Firefly Algorithm (SA-GSO) for multi-objective fish school behavior in human-machine collaborative disassembly sequence planning, the Bee Colony Algorithm (ABC), Traditional Firefly Algorithm (FA), and PSO are widely used in disassembly sequence planning. Now, the SA-FA algorithm is compared with this algorithm to verify the effectiveness of the FA-GSO algorithm. The brightness in the firefly update formula is 0.4, the brightness ratio constant is 0.5, the step size is s0.2, the perception radius is 0r2.05, the decision radius update formula is 1.0, and the neighborhood width value is set to 5.

This article uses IGD and HV representation algorithms for human-machine collaborative disassembly sequence planning to measure the convergence and effectiveness of the algorithm by approximating the non-dominated solution set (PF *) of Pareto and the actual Pareto front (PF). To verify the effectiveness of the firefly algorithm for Pareto fish school behavior, the average HV and IGD values were compared for different iterations with the same initial population of 100.

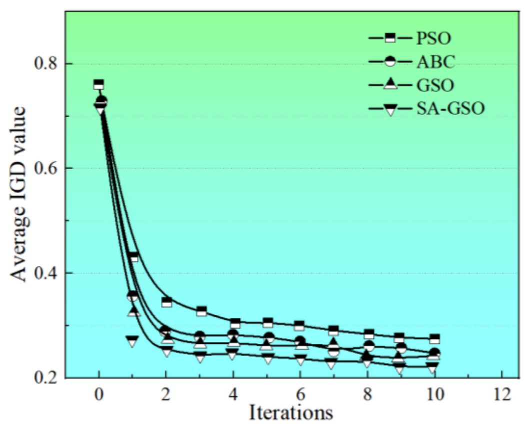

Figure 6. Neural network proton model

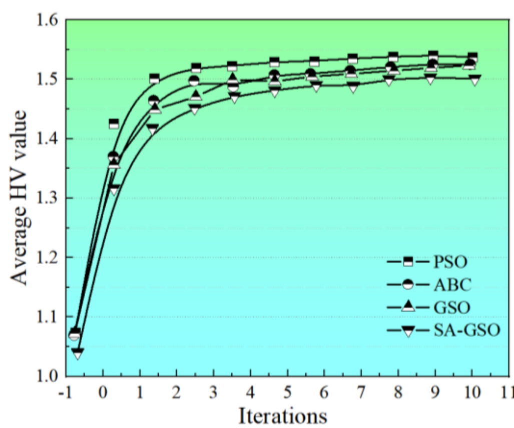

Figure 7. Neural network proton model

The results are shown in Figures 6 and 7. The firefly algorithm for Pareto fish school behavior has certain advantages in HV and IGD under specific population sizes and iteration times of biosensors. The firefly algorithm for Pareto fish school behavior has effectiveness and superiority in solving human-machine collaborative disassembly sequences.

Based on the collected disassembly information, a product disassembly hybrid diagram is established using PBS disassembly based on human-machine cooperation. Multi-objective optimization is performed on the firefly algorithm for fish behavior, with disassembly cost, difficulty, and time as optimization indicators. Then, performance metrics are used to compare and analyze similar algorithms, and finally, the optimal PBS human-machine cooperation disassembly sequence is obtained.

Safety Prediction of Dismantling Waste Lithium Batteries

To predict the safety of dismantling waste lithium batteries of biosensors within the enterprise, this article first collected several commonly used processes and historical data related to dismantling waste lithium batteries. After removing invalid data and repairing missing data, a total of 60 sets of safety and characteristic factor data of dismantling waste lithium batteries were obtained to form a dataset, including 20 sets of battery pack level, module level, and cell unit level, as shown in Table 5, The symbols in the table are explained in Table 6.

Table 5. Historical data of lithium battery disassembly process in a certain enterprise

Number of groups	X1	X2	X3	X4	X5	X6	Y(/%)
1	300	75	2.7	73	0.8	0.9	0.492
2	302	75	2.88	73	26.6	0.89	0.349
...							
20	310	76	3.6	84	20.4	0.57	0.574

Table 6. Explanation of symbols

	X1	X2	X3	X4	X5	X6	Y
illustrate	Storage capacity	SOH	Physical failure characteristics	Electrical conductivity of dismantling tools	Heat dissipation performance of disassembly tools	Disassembly position and direction	Probability of dismantling hazards

Conclusion

Experts endeavor to enhance systems in several energy issues by identifying the key factors that govern the system's results. The variables are called decision factors, while the system's results are termed function objectives. This article explores the performance impact of neural network optimization on the disassembly sequence of lithium batteries in network coding. Through experiments and analysis, the following conclusions have been drawn:

The research analyzed the PBS disassembly process. Analyze the connection methods and materials between the internal components of PBS, elaborate on the disassembly task method, disassembly operation mode, and disassembly tool angle to classify PBS disassembly, then draw the PBS disassembly process, analyze the disassembly characteristics of components in the disassembly process, and finally construct a PBS disassembly process framework to prepare for the subsequent human-machine cooperation disassembly sequence task allocation.

The research found that neural network optimization can significantly improve the efficiency and accuracy of lithium battery disassembly sequences in network coding. The research observes that under different datasets and model settings of biosensors, neural networks can learn different disassembly order patterns, which have different impacts on the disassembly of lithium batteries. This indicates that applying neural networks in network coding has a certain degree of flexibility and adaptability.

The performance impact of neural network optimization on the disassembly sequence of lithium batteries in network coding is closely related to the parameter settings of biosensors. The performance impact of neural network optimization on the disassembly sequence of lithium batteries in network coding has broad application prospects.

The effective use of machine learning will promote chemical sustainability, improve sensor efficiency, and comprehensively expedite intricate electrochemical biosensor utilization. Future endeavors will incorporate diverse characteristics for additional biosensors into this envisioned system. The output of the suggested method is evaluated using many databases and other deep learning methods.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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