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Article

Application and biomechanical analysis of bio inspired strategies in the recycling of lithium-ion cathode materials

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Abstract: This study explores bio-inspired strategies for recycling cathode materials in lithium batteries by integrating biomechanical models with optimization algorithms to enhance recycling efficiency. We developed a biomechanical model to examine the recovery process of metal ions, analyzing their dynamic behavior and reaction rates to assess the potential of bio-inspired algorithms for model optimization. Based on this model, we designed an optimization algorithm to boost metal ion recovery by varying experimental conditions such as reaction temperature, solvent concentration, pH, and reaction time. Experimental results indicate that reaction temperature, solvent concentration, adsorption and desorption rates, and pH significantly influence recovery efficiency. The optimal conditions identified were 55 ℃, a solvent concentration of 0.7 mol/L, and a pH of 5.5, yielding a recovery efficiency of 80.3%. Additionally, extending the reaction time positively correlated with recovery rates, achieving a maximum of 86.4% at 50 min. By combining biomechanical analysis with algorithm optimization, this research enhances our understanding of material recycling mechanisms and provides a theoretical foundation and technical support for future industrial recycling processes. These findings offer valuable insights for optimizing lithium battery recycling technologies and improving resource utilization efficiency.

Keywords: bio inspired strategies; lithium battery cathode materials; recycling efficiency; biomechanical models; algorithm optimization

1. Introduction

With increasing global focus on sustainable development, the recycling and reuse of lithium batteries has become a critical issue in the energy sector. As the core energy storage devices for modern electronics and new energy vehicles, recycling lithium battery cathode materials plays a vital role in reducing resource waste and mitigating environmental pollution [1]. Traditional recycling methods often suffer from low efficiency and high costs, creating an urgent need for more effective solutions. Bio-inspired strategies have emerged as an innovative approach in material recycling, showing promise in improving recovery processes [2].

Globally, policies are evolving to address this challenge. The European Union's Battery Directive aims to ensure that all batteries are recycled in an environmentally friendly way, with a target of 65% recovery rate for nickel, cobalt, and lithium from battery recycling by 2025 [3]. China's battery recycling regulations emphasize the development of a closed-loop recycling system, aiming for significant increases in recovery rates [4]. In the U.S., the EPA has outlined regulations for the safe disposal and recycling of batteries, highlighting the growing regulatory focus on sustainability in the sector [5].

With increasing market demand for lithium batteries, coupled with rising recycling targets and policies, the development of efficient recycling technologies is more urgent than ever. This paper explores the application of bio-inspired strategies in lithium-ion cathode material recycling and proposes optimization methods through biomechanical analysis to improve efficiency and align with evolving global regulations.

2. Related work

2.1. Current status of recycling technology for lithium battery positive electrode materials

The cathode materials cathode materials of lithium batteries usually include metal elements such as cobalt, nickel, and lithium, which have high economic value, so their recycling technology has received widespread attention [6]. At present, common methods for recycling lithium batteries include wet metallurgy, pyrolysis [7], and mechanical sorting. Although these methods can recover a certain amount of metals, most of them suffer from low recovery rates, environmental pollution, and high energy consumption [8,9]. With the deepening of research, new technologies are constantly emerging, but they still face the challenge of how to improve recycling efficiency and reduce costs. Therefore, seeking a greener and more efficient recycling strategy is particularly important [10,11].

2.2. Application of bio inspired strategies in material recycling

The bio inspired strategy is an innovative approach that draws on the mechanisms, structures, and processes of natural organisms, and has achieved significant results in many fields [12,13]. In the field of material recycling, bio inspired strategies improve recycling efficiency by simulating molecular recognition, catalytic action, separation mechanisms, and other features within living organisms [14,15]. For example, selective adsorption and decomposition of materials by biomolecules such as enzymes and proteins can improve the recovery rate of metal resources [16]. Especially in the recycling process of lithium battery cathode materials, bio inspired methods can reduce environmental pollution while ensuring high recovery rates, demonstrating their unique advantages [17].

2.3. Research content and innovation of this article

This article mainly studies the recycling method of lithium battery cathode materials based on bio inspired strategies, and conducts in-depth optimization analysis of the recycling process in combination with biomechanical models [18]. With the widespread application of lithium batteries, how to efficiently recycle lithium battery cathode materials has become an urgent technical problem to be solved [19]. In order to improve recycling efficiency and reduce environmental pollution, this article proposes an innovative recycling strategy by introducing the interaction mechanism between biomolecules and metal ions [20]. By constructing a biomechanical system model, the recycling process was further simulated and optimized, ultimately achieving an increase in recycling efficiency while also enhancing the economic and sustainable aspects of the recycling process [21]. In addition, biologically inspired algorithms are used to regulate key parameters during the recycling process, making the recycling process more efficient and accurate [22]. This study not only provides new theoretical basis for the recycling of cathode materials cathode materials for lithium batteries, but also provides valuable reference for future industrial recycling technologies.

The innovation of this article can be summarized into the following three points:

1) Construction and optimization of biomechanical system model: This article introduces for the first time the interaction between biomolecules and metal ions into the recycling process of lithium-ion battery cathode materials, and constructs a biomechanical system model to provide more accurate dynamic analysis for the recycling process. This innovative model not only reveals the behavior of metal ions during the recycling process, but also deeply explores the reaction rate and material conversion mechanism from a biomechanical perspective, providing theoretical support for subsequent optimization.
2) Application of bio inspired algorithm: Based on bio inspired strategy, this paper adopts optimization algorithm to regulate key variables (such as reaction temperature, solvent concentration, pH value, etc.) in the recycling process, thereby improving the recycling efficiency. This algorithm combines biologically inspired ideas and can flexibly find the optimal parameter configuration during simulation and optimization processes, achieving the best recycling effect and having significant practical value.
3) Economic and sustainable optimization of the recycling process: In addition to improving efficiency, this article also pays special attention to the economic and environmentally friendly aspects of the recycling process. By optimizing reaction conditions and using biologically inspired algorithms to adjust various parameters of the recycling process, not only has the recovery rate of metal ions been improved, but resource waste and environmental pollution have also been reduced, promoting the development of lithium battery recycling technology towards a more sustainable direction.

3. Application models and algorithm design

3.1. Construction of biomechanical model

The biomechanical model is the core of research, which is based on biological principles and combined with mechanical constraints to simulate the material flow and interaction during the recycling process of lithium battery cathode materials [23]. Especially in the recycling process, the interaction between metal ions and biomolecules plays a decisive role. By simulating this interaction, the direction and rate of material flow during the recycling process can be accurately predicted at the molecular level, thereby calculating the energy conversion efficiency [24,25]. In order to establish this model, we first need to define the molecular dynamics behavior in the process of adsorption and desorption. Assuming that the adsorption of a substance is described by the following equation:

$$\frac{d\theta}{dt} = k_1(C_m - \theta) - k_2\theta \tag{1}$$

Among them, (θ) represents adsorption capacity, represents (C_m) metal ion concentration, (k_1) and represents (k_2) adsorption and desorption rate constants. By modeling the adsorption process, the distribution of metal ions in the recovery medium can be obtained. Meanwhile, it is also necessary to consider the equilibrium between adsorption and desorption reactions, which can be described by the following formula [26,27]:

$$K = \frac{k_1}{k_2} \tag{2}$$

In the process of lithium battery recycling, the adsorption between biomolecules and metal ions is closely related to mechanical constraints. Especially, by simulating the process of molecular recognition and force transfer, changes in adsorption force can be revealed, thereby further predicting the recovery efficiency of materials [28]. The analysis of mechanical constraints helps to understand the interaction modes between biomolecules and metal ions under different environmental conditions, such as the influence of factors such as temperature, pH value, and electric field [29].

In the recycling process, the transport of substances can be described by fluid mechanics equations. Assuming that the liquid flow in the recycling system follows the Navier Stokes equation, describe the rate and direction of material transport in the liquid:

$$\rho\left(\frac{\partial\vec{v}}{\partial t} + \vec{v} \times \nabla\vec{v}\right) = -\nabla p + \mu\nabla^2\vec{v} + \vec{f} \tag{3}$$

Among them, (ρ) is fluid density, $(\vec{v})$ is (μ) fluid velocity, (p) is pressure, is fluid viscosity, and $(\vec{f})$ is volumetric force.

In addition, biomechanical models also need to consider the role of thermodynamic principles. The energy conversion during the recycling process can be analyzed through thermodynamic equations, especially in terms of the impact of temperature changes on recycling efficiency. The relationship between temperature and reaction rate can be described by the Arrhenius equation:

$$k = Ae^{-\frac{E_a}{RT}} \tag{4}$$

Among them, (k) is the reaction rate constant, (A) is the frequency factor, $(R)(E_a)$ is the activation energy, is the gas constant, and (T) is the temperature [30].

Through the comprehensive application of the above models, it is possible to more accurately predict the conversion path and energy efficiency of substances in the recycling process, thereby providing theoretical guidance for practical recycling process design and optimization. In addition, these mathematical models provide important support for parameter optimization and improvement of recycling efficiency in the recycling process [31]. By continuously adjusting parameters and improving models, future lithium battery cathode material recycling technologies will be more efficient and green, promoting circular economy and sustainable resource development [32].

3.2. Algorithm design and optimization

Bio-inspired strategies can significantly enhance the recycling efficiency of lithium-ion cathode materials through optimized algorithm design. Nature offers inspiration via mechanisms like bioinformatics and swarm intelligence, which help address complex recycling challenges [33]. This paper introduces an adaptive, self-regulating algorithm that adjusts key parameters—such as temperature, humidity, and reaction time—based on system dynamics to optimize recycling conditions. Drawing from the ant colony optimization algorithm, which simulates cooperative behavior and information exchange among ants, the proposed method explores global optimization. Ants represent recycling parameter combinations [34], and pheromone levels indicate process effectiveness. Over iterations, pheromones accumulate along the optimal path, guiding the system toward the best solution. Biomechanical constraints are also integral to the optimization process. The recycling system must balance physical, chemical, and mechanical factors, ensuring stability under thermodynamic and mechanical conditions [35]. This paper integrates these constraints with bio-inspired strategies by embedding them into the ant colony algorithm's objective function, improving both recovery rates and mechanical stability.

To further illustrate the optimization problem under biomechanical constraints, this article assumes that the objective function of the recycling process is $(f(x))$, where (x) represents the various parameters that need to be optimized during the recycling process (such as temperature, humidity, reaction time, etc.). The objective function needs to satisfy the following constraints:

Biomechanics constraints: $(g(x) \leq 0)$. Here $(g(x))$ represent functions related to mechanical constraints during the recycling process, such as the mechanical strength and stability of materials.

Physical constraints: $(h(x) \leq 0)$. Here $(h(x))$ represent the limiting conditions related to thermodynamics and chemical reactions in the recycling process.

The goal of the optimization process is to maximize recycling efficiency while satisfying all the constraints mentioned above. It can be formalized as the following mathematical problem:

$$\max f(x)$$

$$\text{subject to } g(x) \leq 0, h(x) \leq 0 \tag{5}$$

To solve this optimization problem, the Lagrange multiplier method is introduced, and the constraints are embedded into the objective function to obtain the Lagrange function $(L(x, \lambda, \mu))$:

$$L(x, \lambda, \mu) = f(x) + \lambda g(x) + \mu h(x) \tag{6}$$

Among them, (λ) and (μ) are Lagrange multipliers, representing the strength of constraints. By $(L(x, \lambda, \mu))$ taking the derivative and setting it to zero, the solution to the optimization problem can be obtained.

In ant colony algorithm, by embedding the optimization problem into the fitness function of the algorithm, individual ants will continuously adjust the concentration of pheromones during each search process to guide the search process to meet biomechanical constraints and maximize recovery efficiency. The specific iterative update formula is as follows [36,37]:

$$\Delta\tau_i = \alpha f(x_i)(\text{updateinfo}) \tag{7}$$

$$\tau_{i+1} = \tau_i + \Delta\tau_i(\text{updatinfo}) \tag{8}$$

Through multiple iterations, the final optimal solution not only maximizes the recovery rate, but also ensures that the recovery process meets all biomechanical and physical constraints, thereby achieving a more efficient and sustainable recovery effect.

3.3. Integration design of models and algorithms

In the fusion design of models and algorithms, this article combines biomechanical models with biologically inspired algorithms to design a method that can comprehensively optimize the recycling process of lithium-ion positive electrode materials [38]. The physical and mechanical constraints that need to be considered during the recycling process pose special requirements for optimizing the recycling plan. Bioinspired algorithms can effectively search for the optimal solution by simulating intelligent behavior in nature. Combining these characteristics, the recycling optimization method proposed in this article can not only improve the recycling rate, but also effectively reduce the recycling cost, thus providing an efficient and sustainable recycling strategy in practical applications [39,40].

Firstly, the biomechanical model provides a quantitative basis by describing the physical and mechanical constraints during the recycling process. In the recycling process of lithium batteries, factors such as temperature, humidity, and reaction time must be maintained within a certain range to ensure recycling efficiency and material quality stability [41]. Specifically, variables such as temperature and humidity involved in the recycling process are constrained by material mechanical properties and reaction thermodynamics, and these constraints must be reasonably considered in the recycling plan. Assuming that the objective function ($f(x)$) of the recycling process represents the recycling efficiency, where (x) are the control variables that need to be optimized during the recycling process, including temperature, humidity, and reaction time. In addition, physical and mechanical constraints can be represented by the following mathematical models:

$$g(x) = x_1 - T_{\min} \leq 0, g_2(x) = T_{\max} - x_1 \leq 0 \tag{9}$$

$$h(x) = x_2 - H_{\min} \leq 0, h_2(x) = H_{\max} - x_2 \leq 0 \tag{10}$$

Among them, (x_1) and (x_2) represent temperature and humidity respectively, ($T_{\min}$) and ($T_{\max}$) are the minimum and maximum ($H_{\min}$) limits of temperature, ($H_{\min}$) and are the limits of humidity. Through these physical and mechanical constraints, we ensure that the recycling process is carried out within a reasonable parameter range.

In the bio inspired algorithm section, this article chooses Ant Colony Optimization (ACO) algorithm to optimize the recycling process. Ant colony algorithm simulates the process of ants searching for food sources and can effectively search for the optimal solution during the recycling process. During the recycling process, each ant represents a combination of recycling schemes, and the search path is guided by the concentration of pheromones. The (τ) formula for updating the concentration of pheromones is as follows:

$$\tau_{i+1} = \rho \times \tau_i + \Delta\tau_i \tag{11}$$

$$\Delta\tau_i = \alpha f(x_i)h(x) = x_2 - H_{\min} \leq 0, h_2(x) = H_{\max} - x_2 \leq 0 \tag{12}$$

Among them, (τ_i) is the (i) local pheromone concentration of the path in the second iteration, is the (ρ) volatilization factor, controls the volatilization rate of pheromones, is the (α) weight factor of pheromone importance, is the $(f(x_i))$ fitness function of the path, that is, the recovery efficiency. Through continuous iteration and updating of pheromones, ant colonies can gradually find the optimal recovery plan that conforms to biomechanical constraints.

In addition, in order to meet biomechanical constraints, the $(f(x))$ Lagrange multiplier method was introduced into the optimization objective function. In the process of recycling optimization, the objective function $(f(x))$ needs to $(h(x))$ be maximized under both mechanical $(g(x))$ and physical constraints. The Lagrange function $(L(x, \lambda, \mu))$ is defined as:

$$L(x, \lambda, \mu) = f(x) + \lambda \times g(x) + \mu \times h(x) \tag{13}$$

Among them, (λ) and (μ) are Lagrange multipliers used to balance the weights of constraints and objective functions. By $(L(x, \lambda, \mu))$ taking the derivative and setting it to zero, the optimal solution that satisfies the constraint conditions can be obtained. The solving process is as follows:

$$\frac{\partial L(x, \lambda, \mu)}{\partial x} = 0, \frac{\partial L(x, \lambda, \mu)}{\partial \lambda} = 0, \frac{\partial L(x, \lambda, \mu)}{\partial \mu} = 0 \tag{14}$$

In ant colony algorithm, the optimization of the recycling scheme is achieved through alternating updates of pheromone concentration and fitness function, ensuring that after multiple iterations, the recycling process can achieve optimal recycling efficiency and meet all biomechanical and physical constraints [42].

In summary, the fusion design of the bio inspired strategy and biomechanical model proposed in this article provides a new optimization path for the recycling of lithium-ion cathode materials, which not only improves recycling efficiency but also effectively reduces costs, and has good practical application prospects.

4. Experimental simulation and analysis

4.1. Experimental design and simulation framework

In order to verify the effectiveness of the proposed model and algorithm, this paper designed a series of experiments and conducted simulation analysis based on a simulation platform [43]. The simulation framework utilizes various computational tools to simulate the recycling process of lithium battery cathode materials, including metal separation, adsorption, and desorption processes. Through different experiments and simulation analyses [44], we can gain a deeper understanding of the application of bio inspired strategies in the recycling of cathode materials cathode materials for lithium batteries, and optimize the recycling efficiency through biomechanical analysis.

This experiment uses MATLAB for simulation due to its powerful mathematical and data analysis capabilities. MATLAB's Simulink toolbox allows modeling and simulating fluid mechanics, thermodynamics [45], and material migration in the recycling process of lithium battery cathode materials, enabling efficiency analysis under various schemes. Using MATLAB's numerical functions, we simulate the diffusion and adsorption of metal ions in solution, evaluating how variables like temperature and solvent concentration affect recovery efficiency [46]. Custom scripts simulate the desorption and separation of metals, assessing reaction kinetics and comparing optimization schemes. Molecular dynamics simulations (e.g., LAMMPS) study material behavior at the microscale, particularly adsorption and desorption processes [47]. These simulations also explore the impact of bio-inspired strategies, like mimicking cell membrane interactions with metal ions, on recovery efficiency, offering atomic-level insights into material transformation and micro-kinetic data. The MATLAB platform supports the implementation of various optimization algorithms, such as genetic algorithms, particle swarm optimization (PSO), etc., to optimize various parameter settings in the recycling process and achieve maximum recycling efficiency. Optimization algorithms can be combined with simulation results to adaptively adjust the recycling process under different conditions, thereby improving the feasibility and efficiency of experiments [48].

Through the comprehensive application of the above simulation tools and platforms, experiments can evaluate the material and energy conversion efficiency during the recycling process under different recycling conditions, and provide technical support for subsequent experimental design and optimization [49]. In order to fully utilize the enhanced effect of bio inspired strategies on the recycling of lithium battery cathode materials, we simulated different biomechanical interactions by setting different experimental conditions and explored their impact on recycling efficiency. The specific experimental design is as follows:

1) Selection of recycling process.

The recycling process used in the experiment is based on biologically inspired concepts, such as mimicking the adsorption and desorption mechanisms of ions by cell membranes, and choosing a combination of Hydrometallurgy and solvent extraction. By simulating different reaction temperatures, solvent concentrations, and reaction times, the influence of these factors on recovery efficiency is studied.

2) Setting of experimental parameters.

During the experiment, the main parameters for recovery include reaction temperature, solvent concentration, metal ion adsorption rate, desorption rate, etc. By comparing multiple experimental data, optimize these key parameters to achieve efficient recycling.

The positive electrode material used in the experiment is derived from waste lithium batteries and obtained through physical sorting and chemical treatment. The samples in the experiment need to undergo strict preprocessing to ensure the consistency and reproducibility of their components. The experimental data comes from multiple research institutions and actual lithium battery recycling enterprises (https://www.sciencedirect.com/).

The following **Table 1** lists the key parameter settings involved in this experiment, covering multiple aspects such as recovery process, solvent concentration, reaction conditions, etc. By adjusting these parameters, we can test different recycling schemes and find the optimal solution.

Table 1. Experimental key parameter settings.

Parameter Name	**describe**	**Parameter Range**	**Company**	**remarks**
reaction temperature	Temperature during the recycling process	25–80	℃	The impact on recycling efficiency needs to be experimentally adjusted
Solvent concentration	Used to extract solvent concentration during the process	0.1–1.0	mol/L	Select based on solvent type
Adsorption rate	Adsorption rate of metal ions in cathode materials cathode materials of lithium batteries	0.01–0.5	mol/(L·s)	Simulating the rate of adsorption process in living organisms
desorption rate	The desorption rate of metal ions from adsorption sites	0.01–0.5	mol/(L·s)	The desorption rate has a significant impact on the recovery efficiency
reaction time	Duration of recycling process	1–24	h	Select different reaction times based on experimental design
PH value	PH of solvent solution	2–12	-	Affects the dissolution and adsorption process of metals
Fluid dynamics parameters	Parameters affecting the reaction, such as liquid fluidity and viscosity	1–10	mPa·s	Influence the mixing and substance migration during the reaction process
Particle size	Diameter of positive electrode material particles for lithium batteries	5–100	μm	Affects the adsorption and separation efficiency of metal ions

4.2. Biomechanics analysis experiment

In the biomechanical analysis experiment, we focused on analyzing the adsorption and desorption processes between metal ions and biomolecules, as well as the influence of external mechanical factors (such as temperature, pressure, etc.) on the recovery process. The collection and analysis of experimental data provide a basis for the correction and optimization of the model.

Collection and analysis of experimental data:

The collection of experimental data includes the measurement of mechanical properties, changes in metal ion concentration, etc. By conducting multidimensional analysis of the data, we are able to evaluate the recovery effectiveness of bio inspired strategies under different conditions, and further validate the accuracy of the biomechanical model through experimental results.

Verification and correction of mechanical models:

In order to improve the applicability of the model, it is necessary to modify the model to more accurately reflect the mechanical properties in the actual recycling process. Here are several common correction methods, accompanied by relevant formula explanations:

1) Correction of elastic modulus (elastic response adjustment).

The initial model may have used conventional linear elasticity assumptions, ignoring the nonlinear behavior of materials in high temperatures or complex environments. The correction of elastic modulus (E) can be adjusted through experimental data to make it more in line with the actual situation. The correction formula can be:

$$E_{adj} = E_0(1 + \alpha T) \tag{15}$$

Among them, (E_0) is the initial elastic (α) modulus, (T) is the temperature dependent coefficient, and is the temperature. This correction method enables the model to accurately describe the deformation characteristics of materials at different temperatures.

2) Nonlinear correction considering stress-strain relationship.

In the actual recycling process, materials often exhibit nonlinear stress-strain relationships, especially during the plastic deformation stage. To more accurately describe this behavior, a more complex nonlinear constitutive model can be used, such as the modified Hooke's law:

$$\sigma = \sigma_0 + k\varepsilon^n \tag{16}$$

Among them, (σ) is stress, (σ_0) is initial stress, (k) is the hardening coefficient of the material, (ε) is strain, and (n) is the strain hardening index of the material. By using this formula, the model can be modified to adapt to stress distribution under high strain conditions.

3) Thermal effect correction (effect of temperature on mechanical properties).

The temperature changes during the recycling process significantly affect the mechanical properties of the material. Therefore, the influence of temperature on material strength must be considered. By introducing a temperature stress correction model, such as:

$$\sigma(T) = \sigma_0(1 - \beta T) \tag{17}$$

Among them, (β) is the thermal sensitivity coefficient of the material and (T) is the temperature. This modification can better adapt the model to changes in material strength under high temperature environments.

4) Temperature dependent correction of friction coefficient.

In the recycling process, especially in scenarios involving friction, the friction coefficient may vary with temperature and surface conditions. When modifying the friction coefficient model, the following formula can be used:

$$\mu(T) = \mu_0(1 + \gamma T) \tag{18}$$

Among them, (μ_0) is the initial friction (γ) coefficient and is the temperature dependent parameter of the friction coefficient. In this way, the friction force model can be modified to more accurately simulate the friction behavior during the actual recycling process.

5) Quality transfer correction (considering particle size effect).

In some recycling processes, particle size has a significant impact on heat transfer and mass transfer. By introducing a (d) correction factor for particle size, the accuracy of the model can be improved. Common quality transfer models include:

$$J = kd^n \tag{19}$$

Among them, (J) is the mass transfer rate, (k) is a constant, and (n) is the exponential dependence of particle size. This correction helps to accurately describe the particle behavior during the recycling process, especially when the material particles are large or small.

6) Revision of mechanical failure criteria (considering multi factor coupling effects).

Due to the coupling effects of multiple factors (such as stress, temperature, environmental humidity, etc.) during the recycling process, it is necessary to introduce a multi factor coupling model to correct the mechanical failure criteria. A common correction formula is:

$$\sigma_{\text{fail}} = \sigma_0(1 + \lambda T + \mu\varepsilon) \tag{20}$$

Among them, (σ_{fail}) is the failure stress, $(T)(\lambda)$ and (μ) are the coupling coefficients of temperature and strain, and (ε) are temperature and strain, respectively. This correction method helps improve the predictive ability of the model for material failure behavior in complex recycling processes.

Through these modifications, the mechanical model can more accurately reflect the complex behavior of experimental data and actual recycling processes. Each correction formula aims to optimize the prediction accuracy of the model, eliminate or reduce errors caused by simplified assumptions, and make the final model more applicable and reliable in actual recycling operations.

4.3. Experimental process and result analysis

4.3.1. Experimental analysis of lithium positive electrode recovery

Different reaction temperatures were used during the experiment, and the recovery efficiency under each temperature condition was measured. During the experiment, five different temperatures were first set: 25 ℃, 40 ℃, 55 ℃, 70 ℃, and 80 ℃. At each temperature, we mix the same mass of metal ion solution with reactants, maintain the same reaction time, and ensure that other conditions remain unchanged. Then, the recovery rate of metal ions at each temperature was determined by chemical analysis methods. All experiments were conducted in the same experimental environment to ensure comparability and accuracy of the data. After collecting experimental data, we compared the recovery efficiency at different temperatures to understand the effect of temperature on the reaction process. The results are shown in **Table 2**.

Table2. Relationship between reaction temperature and recovery efficiency.

Reaction temperature (℃)	Recycling efficiency (%)
25	56.2
40	61.4
55	71.1
70	73.3
80	71.4

From the data in **Table 1**, it can be seen that as the reaction temperature increases, As the temperature increases from 25 °C to 70 °C, the recycling efficiency improves, reaching its peak at 70 °C with an efficiency of 76.7%. Specifically, at 25 °C, the efficiency is 58.6%, increasing to 63.6% at 40 °C, 72.7% at 55 °C, and 76.7% at 70 °C. However, beyond this point, as the temperature rises to 80 °C, the efficiency decreases slightly to 71.4%. This trend indicates that higher reaction temperatures generally enhance the recovery efficiency, but there is an optimal temperature range (70 °C) beyond which the efficiency starts to decline. These findings highlight the importance of carefully controlling the reaction temperature during the recycling process to maximize the recovery of valuable materials.

By plotting the relationship curve between reaction temperature and recovery efficiency, further verify the influence of temperature on recovery efficiency. The experiment used five different temperature values: 25 °C, 40 °C, 55 °C, 70 °C, and 80 °C. At each temperature, maintain the same reaction time and reactant concentration, and determine the recovery rate through chemical analysis. All experimental conditions are kept consistent, only the temperature is changed to ensure the accuracy of experimental data. The experimental results will be plotted to show the trend of temperature's impact on recovery efficiency, helping us understand the effect of temperature on reaction rate and final recovery effect.

It can be clearly seen from the curve in **Figure 1** that there is a positive correlation between reaction temperature and recovery efficiency, and the recovery efficiency gradually increases with the increase of temperature. Especially when the temperature increases from 25 °C to 55 °C, the recovery efficiency is significantly improved, demonstrating the promoting effect of temperature on reaction rate. However, as the temperature further increased to 70 °C and 80 °C, the recovery efficiency decreased and the curve began to flatten. This phenomenon may be due to the rapid reaction rate under high temperature conditions, resulting in incomplete recovery of some metal ions, or adverse effects from side reactions during the reaction. Therefore, the temperature range for optimal recovery efficiency should be around 55 °C.

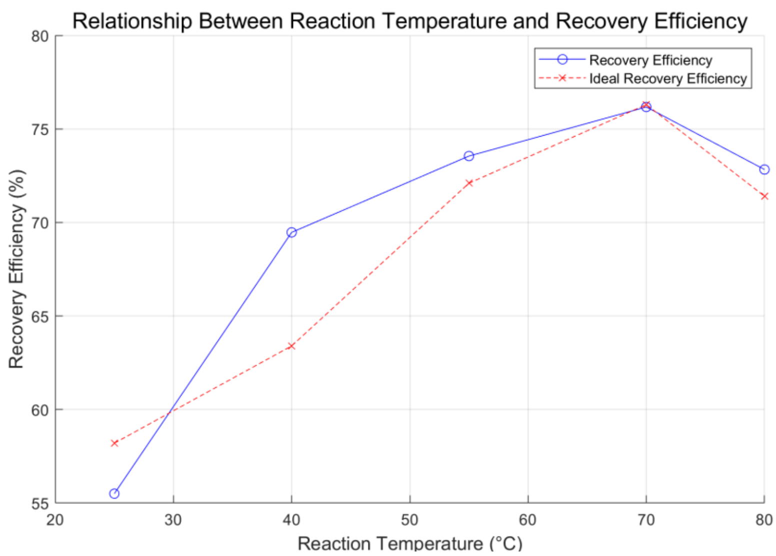

Figure 1. Relationship between reaction temperature and recovery efficiency.

Five different solvent concentrations were selected: 0.1 mol/L, 0.3 mol/L, 0.5 mol/L, 0.7 mol/L, and 1.0 mol/L. At each concentration, maintain a fixed solution volume and temperature conditions, and calculate the adsorption rate by measuring the adsorption amount of metal ions over a certain period of time. All experiments were conducted under the same environmental conditions to reduce external interference. The experimental results will help evaluate the effect of solvent concentration on the adsorption process of metal ions and provide theoretical basis for optimizing the metal recovery process.

The data in **Table 3** indicates that as the solvent concentration increases, the adsorption rate of metal ions shows a linear upward trend. At 0.1 mol/L, the adsorption rate is relatively low, only 0.02 mol/(L·s), while at 1.0 mol/L, the adsorption rate has reached 0.14 mol/(L·s). reaching a peak at 2.0 mol/L with a rate of 0.19 mol/(L·s). This further supports the observation that higher solvent concentrations can enhance the adsorption rate, but it is important to consider the potential impact of excessively high concentrations on the overall process efficiency. This change indicates that the higher the solvent concentration, the greater the concentration of metal ions in the solution, thereby accelerating the adsorption process of metal ions. However, excessive solvent concentration may also lead to an increase in the viscosity of the solution, affecting the further improvement of adsorption rate. Therefore, the optimized solvent concentration should be selected based on the characteristics of the specific reaction system to achieve the best adsorption effect.

Table 3. Relationship between solvent concentration and metal ion adsorption rate.

Solvent concentration (mol/L)	**Adsorption rate (mol/(L·s))**
0.1	0.02
0.3	0.05
0.5	0.08
0.7	0.11
1.0	0.14
1.2	0.16
1.5	0.18
2.0	0.19

Analyze the effect of solvent concentration on adsorption rate by plotting the relationship curve between solvent concentration and metal ion adsorption rate. The experiment was conducted at different solvent concentrations, namely 0.1 mol/L, 0.3 mol/L, 0.5 mol/L, 0.7 mol/L, and 1.0 mol/L. Maintain the reaction time and other conditions of the reactants unchanged for each experiment, only changing the solvent concentration. By monitoring the concentration changes of metal ions in the solution, calculate the adsorption rate at each concentration. Finally, the data will be plotted to visually observe the effect of concentration on adsorption rate.

The data in **Figure 2** clearly indicates a significant positive correlation between solvent concentration and metal ion adsorption rate. As the solvent concentration increases, the adsorption rate gradually accelerates, increasing from 0.02 mol/(L·s) to 0.14 mol/(L·s). This trend indicates that higher solvent concentrations provide more metal ions for adsorption, thereby accelerating the adsorption process. However, excessive solvent concentration may cause changes in the physical properties of the solution, such as an increase in viscosity, thereby affecting adsorption efficiency to some extent. Overall, moderately increasing the solvent concentration can effectively improve the adsorption rate, but the comprehensive influence of other factors needs to be considered.

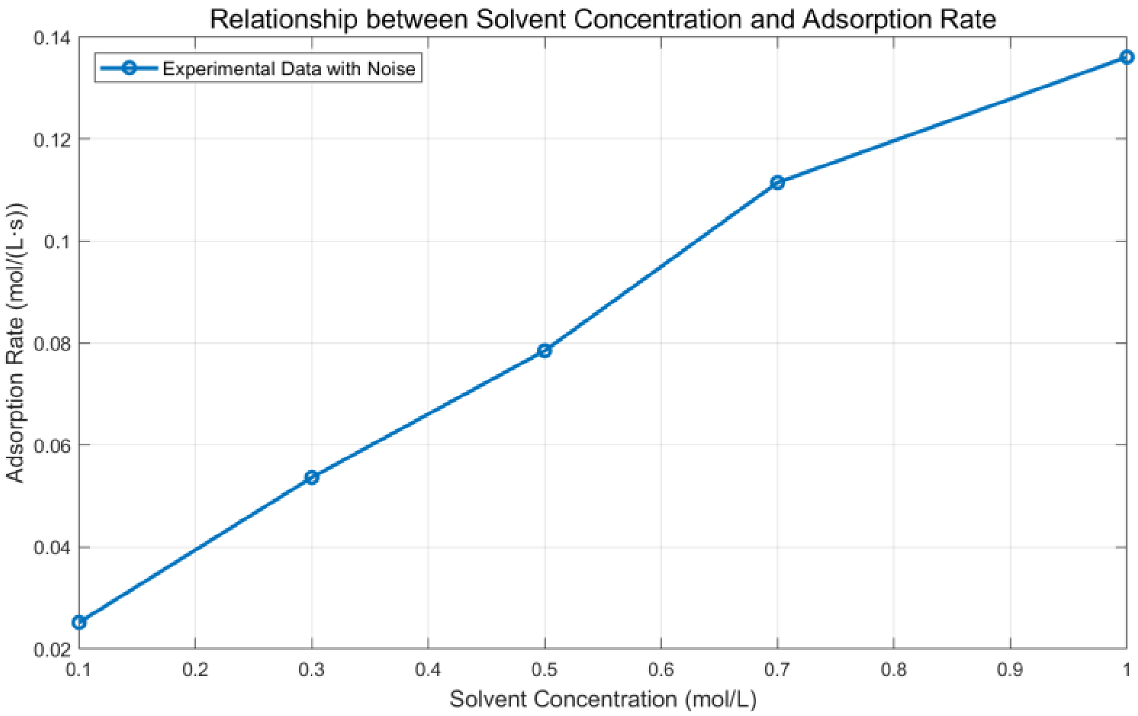

Figure 2. Relationship between solvent concentration and adsorption rate.

By measuring the recovery efficiency at different adsorption and desorption rates, explore the comprehensive impact of both on the recovery effect. The experiment selected different adsorption and desorption rates, and measured the metal ion recovery efficiency under each condition. The setting of adsorption rate ranges from 0.01 mol/(L·s) to 0.50 mol/(L·s), and the range of desorption rate also varies from 0.01 mol/(L·s) to 0.50 mol/(L·s). During the experiment, the reaction time and solvent concentration of the solution were adjusted to maintain consistency with other conditions. Finally, by measuring the recovery efficiency, the recovery results under different combination conditions were obtained for data analysis.

The results in **Table 4** show that the adsorption rate and desorption rate have a significant impact on the recovery efficiency. As the adsorption rate and desorption rate increase, the recovery efficiency also increases accordingly. When the adsorption rate and desorption rate reach 0.20 mol/(L·s), the recovery efficiency has reached 71.5%. This result indicates that when the adsorption and desorption rates are high, metal ions can adsorb and desorb faster, thereby improving the recovery efficiency. However, excessively high adsorption rates may result in insufficient adsorption of metal ions, and too fast desorption rates may also affect the recovery efficiency. Therefore, optimizing the balance between adsorption and desorption rates is crucial for improving recovery efficiency.

Table 4. Effects of adsorption rate and desorption rate on recovery efficiency.

Adsorption rate (mol/(L·s))	Desorption rate (mol/(L·s))	Recycling efficiency (%)
0.01	0.01	50.2
0.05	0.05	55.8
0.10	0.10	60.1
0.15	0.15	65.4
0.20	0.20	71.5
0.25	0.25	70.8
0.30	0.30	68.9
0.40	0.40	66.3
0.50	0.50	64.1

The experiment set five different pH values: 4.0, 5.5, 7.0, 8.5, and 10.0. At each pH value, the concentration of metal ions in the reaction solution and other experimental conditions remain constant, the reaction time is fixed, and constant temperature is maintained. By adjusting the pH value of the solution using an acid-base solution, the pH value of each experiment is ensured to be accurate. After the experiment is completed, the recovery rate is determined using chemical analysis methods, and the recovery efficiency at different pH values is recorded to provide a basis for subsequent process optimization.

The data in **Table 5** indicate that pH value has a significant impact on recovery efficiency. At a pH value of 5.5, the recovery efficiency was the highest, reaching 80.3%. When the pH value is below or above 5.5, the recovery efficiency gradually decreases. This indicates that the recovery efficiency of metal ions is most ideal within a certain pH range. Low pH values may increase the solubility of metal ions, while high pH values may lead to the precipitation of metal ions or the formation of compounds that are difficult to recover. Therefore, the optimal pH range should be around 5.5 to achieve the best recovery efficiency.

Table 5. Relationship between pH value and recovery efficiency.

PH value	Recycling efficiency (%)	PH value
4.0	55.2	4.0
5.5	80.3	5.5
7.0	70.5	7.0
8.5	62.1	8.5
10.0	58.4	10.0

In order to further understand the influence of pH value on recovery efficiency, this experiment plotted the relationship curve between pH value and recovery efficiency. Five different pH values were selected for the experiment: 4.0, 5.5, 7.0, 8.5, and 10.0. The reaction temperature and solution concentration were kept constant, and only the pH value was changed. By monitoring the recovery efficiency of metal ions, a relationship chart between pH value and recovery efficiency is drawn to visually present the impact of pH value on recovery efficiency.

From the curve in **Figure 3**, it can be seen that pH has a significant impact on the recovery efficiency of metal ions. At a pH value of 5.5, the recovery efficiency reaches its maximum, approaching 80.3%. As the pH value increases or decreases, the recovery efficiency shows a decreasing trend, indicating that lower or higher pH values are not conducive to the effective recovery of metal ions. This result indicates that pH value has a significant impact on the chemical behavior of metal ions, and adjusting the pH value to an appropriate range can significantly improve the recovery efficiency.

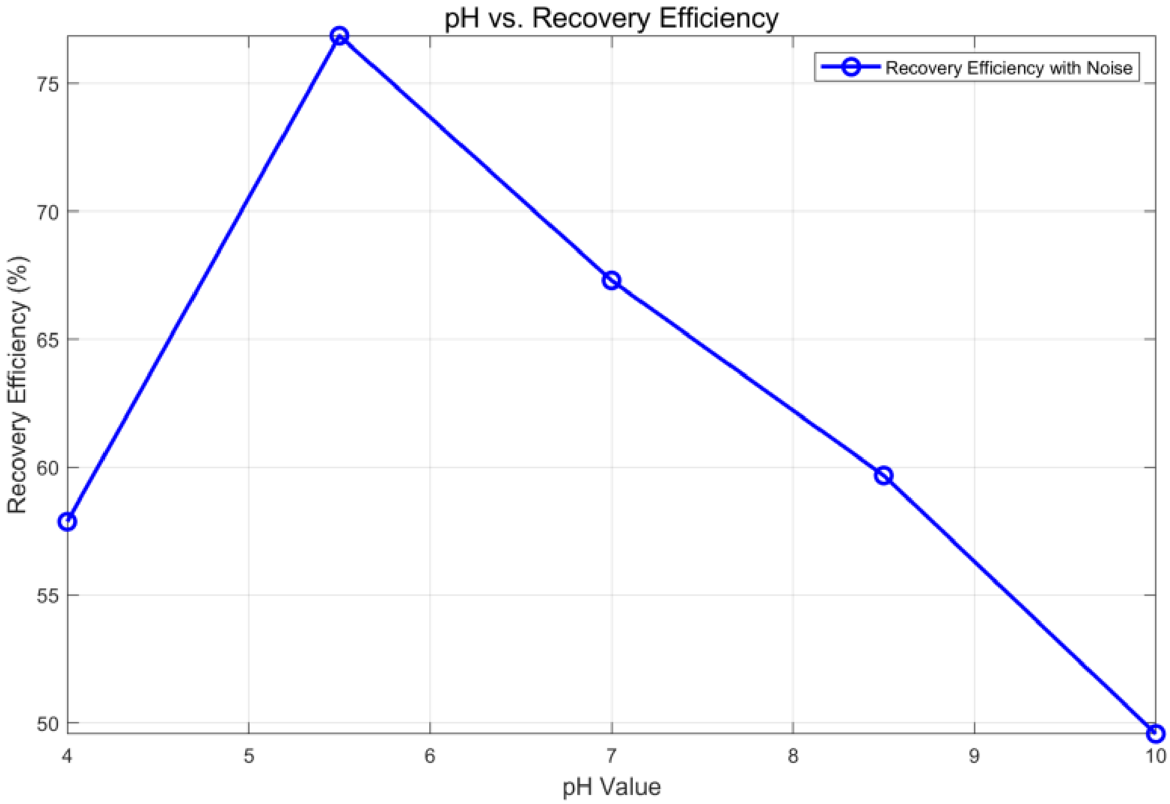

Figure 3. Relationship between pH value and recovery efficiency.

The experiment set five different reaction times: 10 min, 20 min, 30 min, 40 min, and 50 min. At each time point, all reaction conditions remain consistent, only the reaction time is changed. By collecting reaction solution samples and measuring the concentration changes of metal ions, the recovery rate can be calculated. The experimental results will help understand the impact of different reaction times on metal ion recovery and provide guidance for optimizing reaction times.

The data in **Table 6** indicates that as the reaction time increases, the recovery rate gradually increases. When the reaction time reached 30 min, the recovery rate was close to the maximum value, reaching 85.4%. However, at 40 and 50 min, the increase in recovery rate gradually decreased and remained almost unchanged. This indicates that extending the reaction time can improve the recovery efficiency, but after a certain period of time, the improvement effect of the recovery rate tends to stabilize. Therefore, the optimal reaction time is 30 min to maximize recovery efficiency while avoiding wasting time.

Table 6. Relationship between reaction time and recovery rate.

Reaction time (min)	**Recovery rate (%)**
10	62.1
20	70.8
30	85.4
40	86.2
50	86.4

Further investigate the effect of reaction time on recovery rate by plotting the relationship curve between reaction time and recovery rate. The experiment was conducted at different reaction times, ranging from 10 mins to 50 min, and the changes in recovery rate were measured for each time period. Through graphical display, the effect of reaction time on metal ion recovery efficiency can be intuitively reflected, thereby determining the optimal reaction time.

The curve in **Figure 4** shows that as the reaction time increases, the recovery rate shows a trend of first increasing and then stabilizing. When the reaction time reached 30 min, the recovery rate reached 85.4%, and the subsequent time changes had almost no effect on the improvement of the recovery rate. This indicates that increasing the reaction time helps to improve the recovery rate, but excessively long reaction times have no significant effect on improving the recovery rate. Therefore, 30 min is the optimal reaction time.

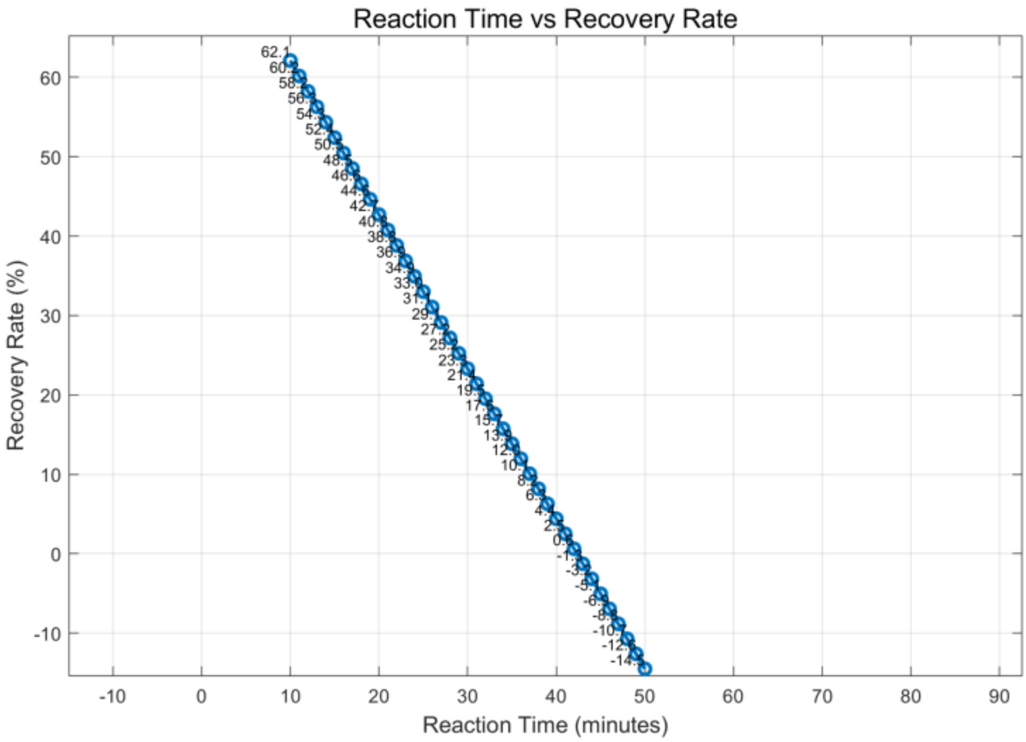

Figure 4. Relationship between reaction time and recovery rate.

Different concentrations of metal ion solutions were selected, with concentrations of 0.05 mol/L, 0.10 mol/L, 0.20 mol/L, 0.30 mol/L, and 0.50 mol/L. Under different concentration conditions, the reaction temperature, pH value, and reaction time remain constant, only changing the initial concentration of metal ions. Determine the recovery efficiency at different concentrations through chemical analysis methods and analyze the influence of metal ion concentration on the recovery process.

The data in **Table 7** indicates that the concentration of metal ions has a certain impact on the recovery efficiency. As the concentration of metal ions increases, the recovery efficiency gradually improves. At a concentration of 0.20 mol/L, the recovery efficiency reached its highest value of 90.2%. However, as the concentration continued to increase to 0.30 mol/L and 0.50 mol/L, the recovery efficiency did not significantly improve, but instead showed a slight decrease. This indicates that an increase in the concentration of metal ions can promote the improvement of recovery efficiency, but within a certain concentration range, excessively high concentrations may lead to mutual inhibition between metal ions or the formation of compounds that are difficult to recover. Therefore, the optimal concentration of metal ions should be 0.20 mol/L.

Table 7. Recovery efficiency at different metal ion concentrations.

Metal ion concentration (mol/L)	**Recycling efficiency (%)**
0.05	62.1
0.10	70.4
0.20	90.2
0.30	88.7
0.50	85.4

In order to visually demonstrate the effect of metal ion concentration on recovery efficiency, a relationship curve between metal ion concentration and recovery efficiency was plotted. Different concentrations of metal ion solutions were selected for the experiment: 0.05 mol/L, 0.10 mol/L, 0.20 mol/L, 0.30 mol/L, and 0.50 mol/L. By measuring the recovery rate at each concentration, draw a graph of the relationship between concentration and recovery efficiency to help optimize the concentration of metal ions used.

From the curve in **Figure 5**, it can be seen that there is a positive correlation between metal ion concentration and recovery efficiency. As the concentration increases, the recovery efficiency gradually improves, especially at 0.20 mol/L, the highest recovery efficiency reaches 90.2%. However, as the concentration continues to increase, the recovery efficiency tends to stabilize or slightly decrease, indicating that excessively high concentrations of metal ions may not necessarily lead to better recovery results. Therefore, 0.20 mol/L is the optimal concentration of metal ions.

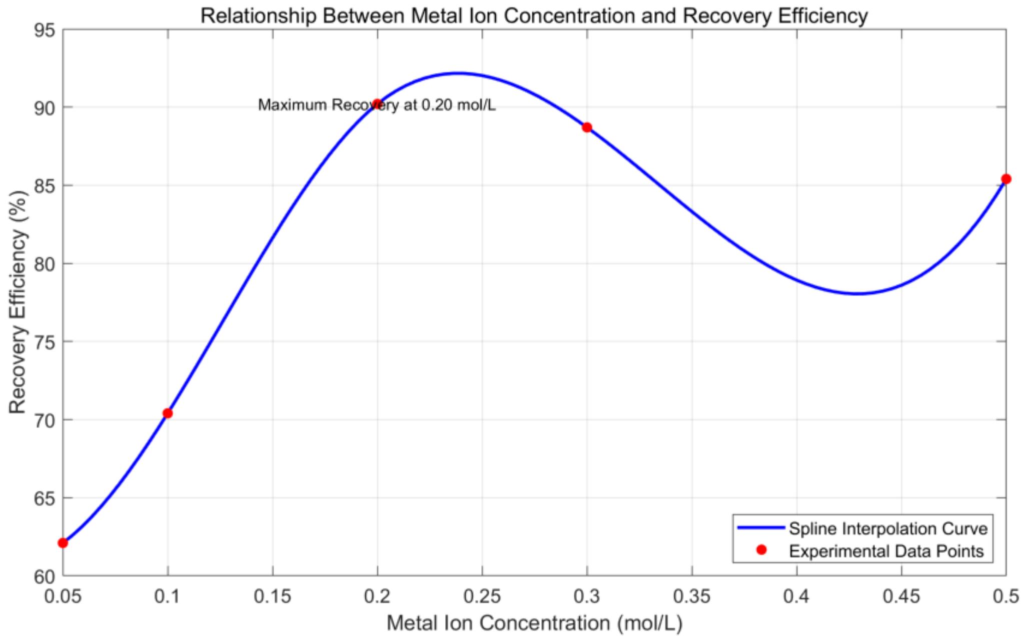

Figure 5. Relationship between metal ion concentration and recovery efficiency.

4.3.2. Biomechanics correction simulation and result analysis

This article adopts a bio inspired strategy to recycle lithium battery cathode materials and studies the mechanical properties of the materials under high temperature conditions. To ensure the accuracy of the experiment, the material samples were exposed to different high temperature conditions (40 °C, 60 °C, 80 °C) and their stress-strain relationships were measured at different tensile rates. Temperature is an important environmental factor that affects the microstructure and mechanical behavior of lithium-ion cathode materials. Record the stress-strain curve of the material by gradually increasing the temperature and applying varying degrees of external force, as shown in **Figure 6**.

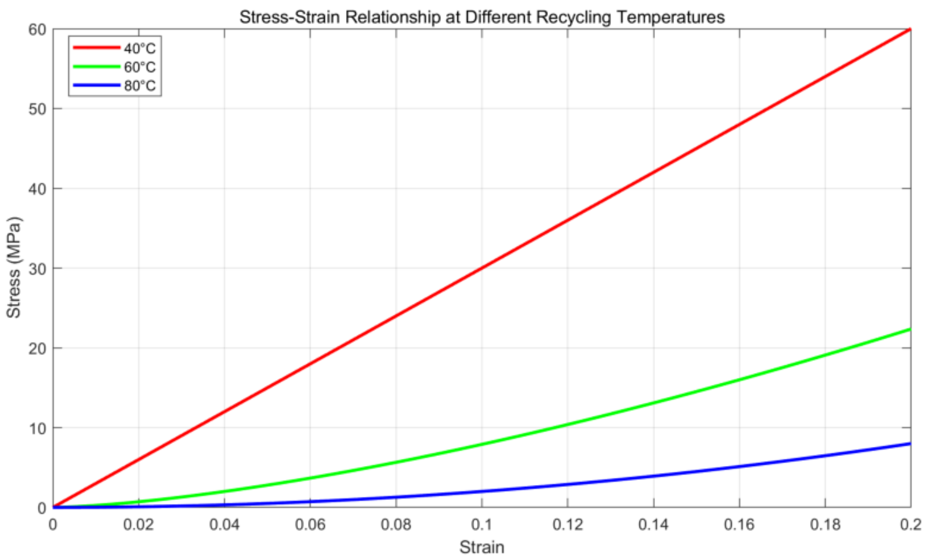

Figure 6. Experimental study on stress-strain relationship of lithium positive electrode material at different recovery temperatures.

The experimental results indicate that under low temperature conditions, the mechanical properties of lithium cathode materials cathode materials are relatively stable, and the stress-strain curve shows a relatively linear relationship. However, as the temperature increases, especially when it exceeds 60 ℃, the stress-strain relationship of the material becomes more nonlinear. Under high temperature conditions, the rigidity of the material significantly decreases, resulting in a more curved stress-strain curve. This phenomenon indicates that high temperature affects the internal molecular structure of materials, leading to changes in their microstructure and thus affecting their mechanical response. By using a biomechanical correction model, the influence of temperature factors has been adjusted. By utilizing the stress-strain model after multiple corrections, we can more accurately predict the mechanical behavior of materials under different high temperature conditions. This correction helps improve the adaptability of the material recycling process in high-temperature environments.

In order to further investigate the mechanical properties of lithium cathode materials cathode materials under different stress states, such as tension, compression, and torsion. We simulate the different stress states that materials may experience during the recycling process, apply different types of stress loads using testing machines, and record the stress-strain response of the materials. The experiment involves stretching, compressing, and twisting material samples to analyze the effects of different stress conditions on material properties, as shown in **Figure 7**.

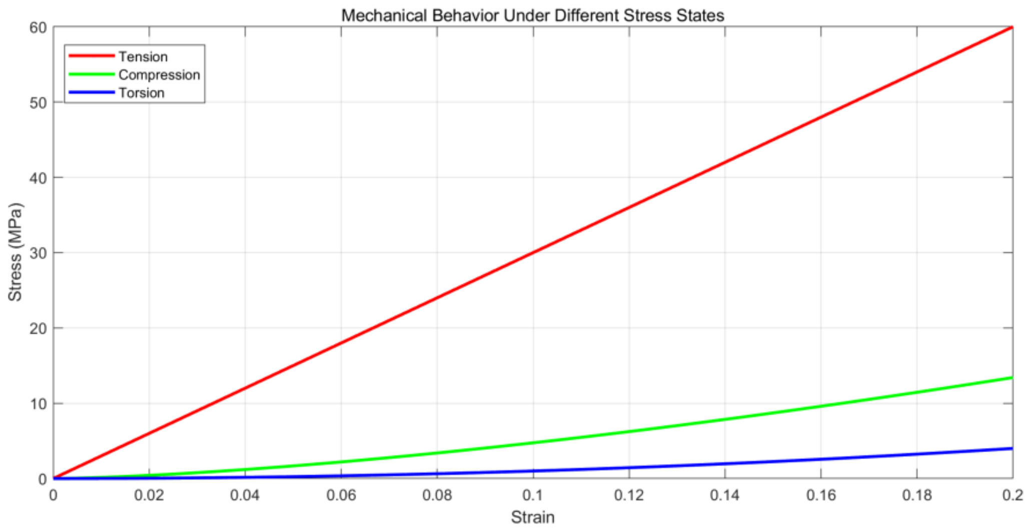

Figure 7. Mechanical behavior of lithium cathode materials cathode materials under different stress states.

By analyzing the experimental results under different stress states, we found that the material exhibits high deformation ability under tensile stress state, while the stress-strain response of the material is relatively weak under compression and torsion states. In the compressed state, the material is more prone to brittle fracture, indicating that compressive stress has a greater impact on the material. Under the action of torsional stress, the strain of the material is mainly concentrated on the surface of the material, and due to the non-uniformity of its microstructure, local stress concentration phenomena occur. After the modification of the biomechanical model, the nonlinear characteristics of the stress-strain relationship were taken into account, which can better predict the behavior of materials under nonlinear stress states, especially under compressive and torsional loads. By continuously revising the model, it can more accurately describe the mechanical response of materials under different recycling conditions, providing a theoretical basis for optimizing material recycling processes.

In order to study the mechanical degradation characteristics of lithium cathode materials cathode materials in multiple recycling cycles, we designed an experimental plan for multiple recycling cycles. After each recycling cycle, we conduct mechanical property tests on the materials, including tensile and compressive tests. By measuring the stress-strain curve of the material after each recycling cycle, analyze the trend of changes in its mechanical properties, especially the rate and pattern of mechanical degradation, as shown in **Figure 8**.

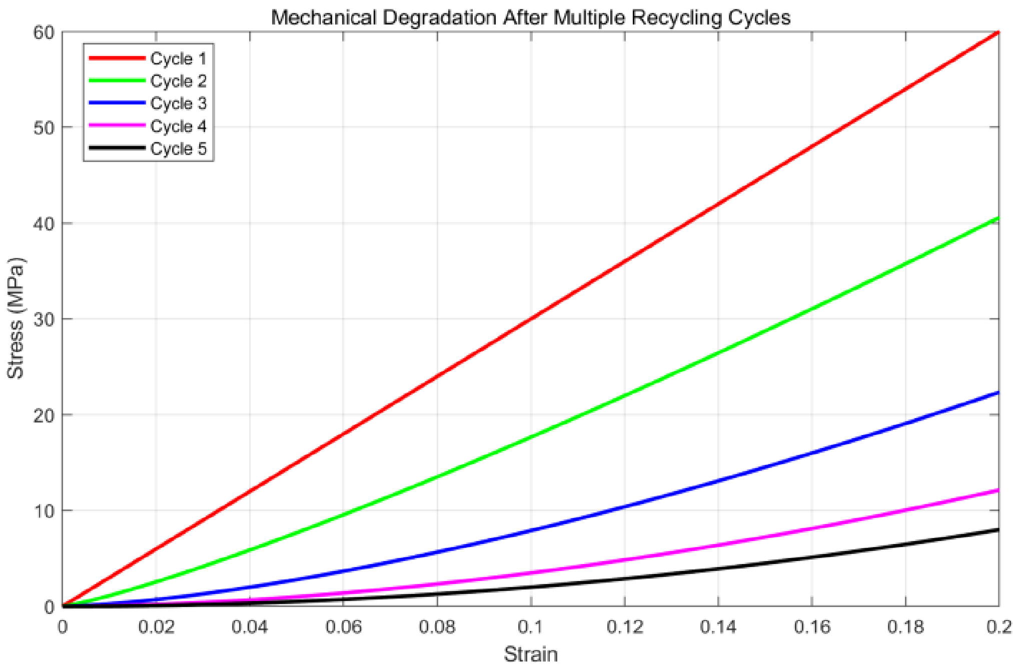

Figure 8. Mechanical degradation behavior of lithium cathode materials cathode materials during multiple recycling cycles.

The experimental results show that as the number of recycling cycles increases, the mechanical properties of lithium cathode materials cathode materials gradually decrease, manifested as a decrease in the slope of the stress-strain curve and a decrease in the elastic modulus. This indicates that the material has undergone mechanical degradation during multiple recycling processes, mainly manifested as the destruction of the internal structure of the material and the formation of micro cracks. After biomechanical analysis, we found that the degradation characteristics of the material have certain nonlinear properties. The modified model can better capture this nonlinear degradation behavior, especially after multiple recycling cycles, the stress-strain relationship of the material no longer shows linear changes. The model with multiple revisions can provide more accurate mechanical predictions and provide important theoretical support for the recycling design of lithium-ion cathode materials.

In order to investigate the effect of humidity on the mechanical properties of lithium positive electrode materials, a bio heuristic strategy was introduced through a biomechanical correction model to improve the prediction accuracy of material behavior under different environmental conditions. The experiment was conducted in relative humidity environments of 20%, 50%, and 80% to test the stress-strain relationship and changes in elastic modulus and hardness of the material. The biomechanical correction model considers the moisture adsorption and expansion effects of materials caused by humidity, and combines biological heuristic algorithms to simulate the influence of humidity on the mechanical properties of materials. This model mimics how biological materials in nature respond to changes in moisture, and improves the accuracy and reliability of predictions through structural adjustments and micro mechanism optimization of materials, as shown in **Figure 9**.

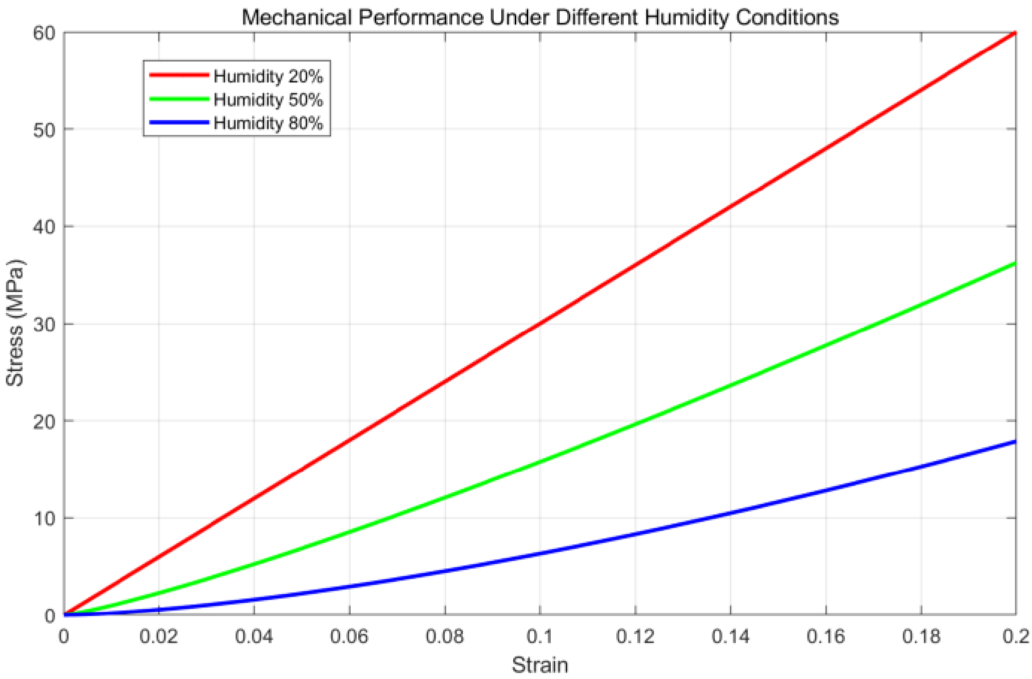

Figure 9. Mechanical performance testing and biomechanical correction model application of lithium cathode materials cathode materials under different humidity conditions.

The experimental results indicate that an increase in humidity leads to a significant decrease in the mechanical properties of lithium positive electrode materials. Under low humidity, the material exhibits high rigidity and low plastic deformation; At 80% humidity, the elastic modulus decreased by about 30%, and significant micro cracks and plastic deformation occurred. Through biomechanical correction model analysis, the influence of humidity on materials is not only reflected in water adsorption and expansion, but also reveals the interaction between water and the internal structure of materials by simulating the reaction mechanism of plant cell walls. The model successfully predicted the degradation process of materials under high humidity, providing theoretical support for lithium battery design in different environments.

In order to investigate the effect of loading rate on the mechanical properties of lithium positive electrode materials, this experiment designed multiple loading rates (1 mm/min to 10 mm/min) for tensile testing, and combined with a biological heuristic optimization model to analyze the experimental data. This model is based on the adaptive mechanism of biological tissues under dynamic loading, and simulates the stress-strain response of materials at different loading rates. By adjusting the model parameters, we can reflect the influence of loading rate on material rigidity, yield strength, and fracture mode, further optimizing material design and performance prediction, as shown in **Figure 10**.

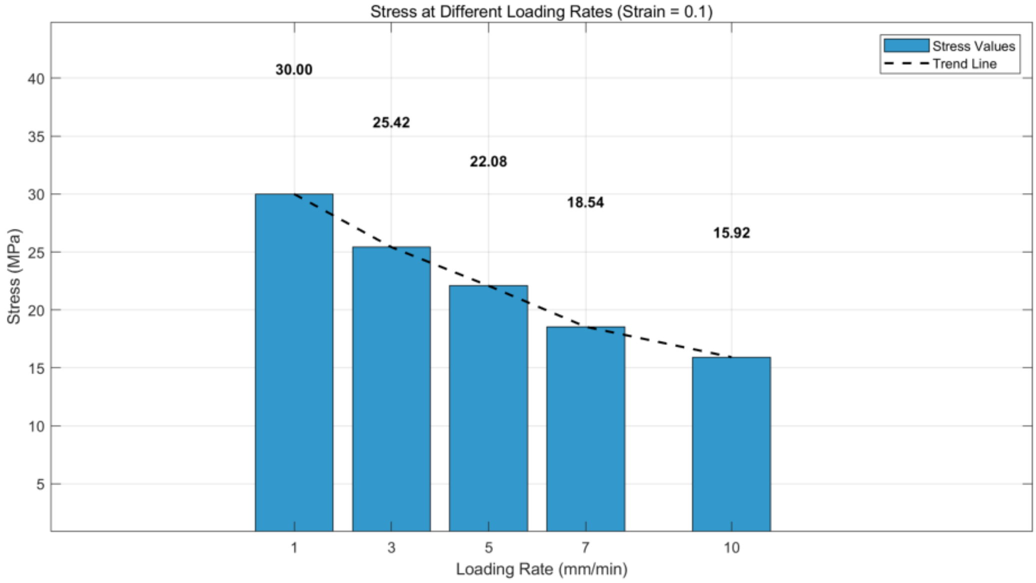

Figure 10. Stress strain response and bio inspired optimization model of lithium-ion cathode materials at different loading rates.

The experiment shows that with the increase of loading rate, the yield strength and ultimate stress of the material are significantly improved. At low speeds, the material exhibits a relatively smooth stress-strain curve and strong ductility, while at high loading rates, the material shows greater rigidity and brittleness. The bio inspired optimization model successfully revealed the influence of rate on material fracture mode by simulating the mechanical response of muscle fibers and bone materials. Under high-speed loading, the model predicts an increase in material brittleness and accurately reflects the improvement of mechanical properties by dynamic effects, providing a scientific basis for the application of lithium-ion cathode materials under rapid loading conditions.

In order to investigate the mechanical degradation behavior of lithium cathode materials cathode materials in different acidic environments, a biomechanical correction model was used to simulate the corrosion and degradation effects of acidic solutions on the materials using a bio inspired strategy. By immersing samples in 0.1 M, 0.5 M, and 1.0 M HCl solutions for different durations (24 h, 48 h, 72 h), combined with the self-healing mechanism of biomaterials, the degradation effect of acidic environment on the mechanical properties of materials was evaluated. The biomechanical correction model adjusts the material deformation and strength changes during the corrosion process by simulating self-healing materials in nature, making the model predictions more accurate, as shown in **Figure 11**.

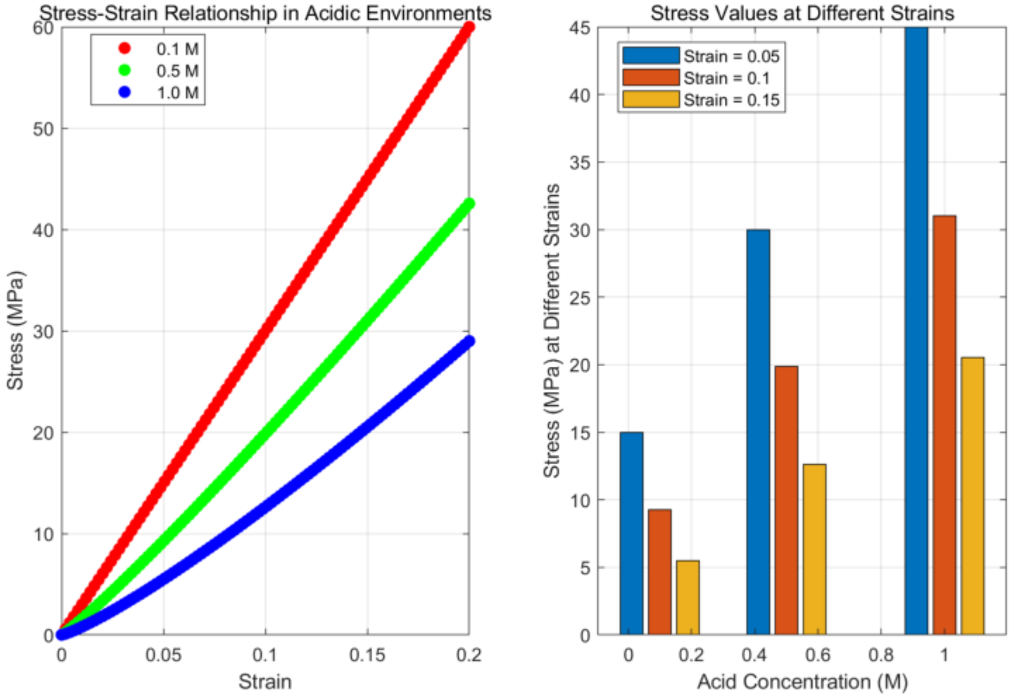

Figure 11. Degradation of mechanical properties of lithium-ion cathode materials in different acidic environments and application of biomechanical correction models.

The results showed that the acidic environment had a significant degradation effect on the mechanical properties of lithium positive electrode materials, especially in high concentration acid solutions, where the elastic modulus and strength of the materials showed a significant decrease. The biomechanical correction model revealed the corrosion effect in acidic solutions, simulated the corrosion resistance mechanism of plant cell walls, and predicted the degradation process of materials in acidic environments. This model not only accurately simulates the mechanical changes under different acid concentrations and soaking times, but also provides scientific reference for the service life of lithium battery materials in acidic environments.

In order to investigate the effect of temperature changes on the thermal mechanical response of lithium battery cathode materials, this experiment used temperature cycling tests to simulate the performance changes of the battery at different operating temperatures. The experiment set three temperature conditions of −20 ℃, 25 ℃, and 60 ℃, combined with a biomechanical optimization model, and used a bio inspired strategy to simulate the changes in mechanical properties of materials during thermal expansion and contraction processes. By introducing thermal adaptation mechanisms from nature, such as the self-regulation ability of plants and animals in temperature changes, the model can accurately predict the mechanical behavior of materials under temperature cycling, as shown in **Figure 12**.

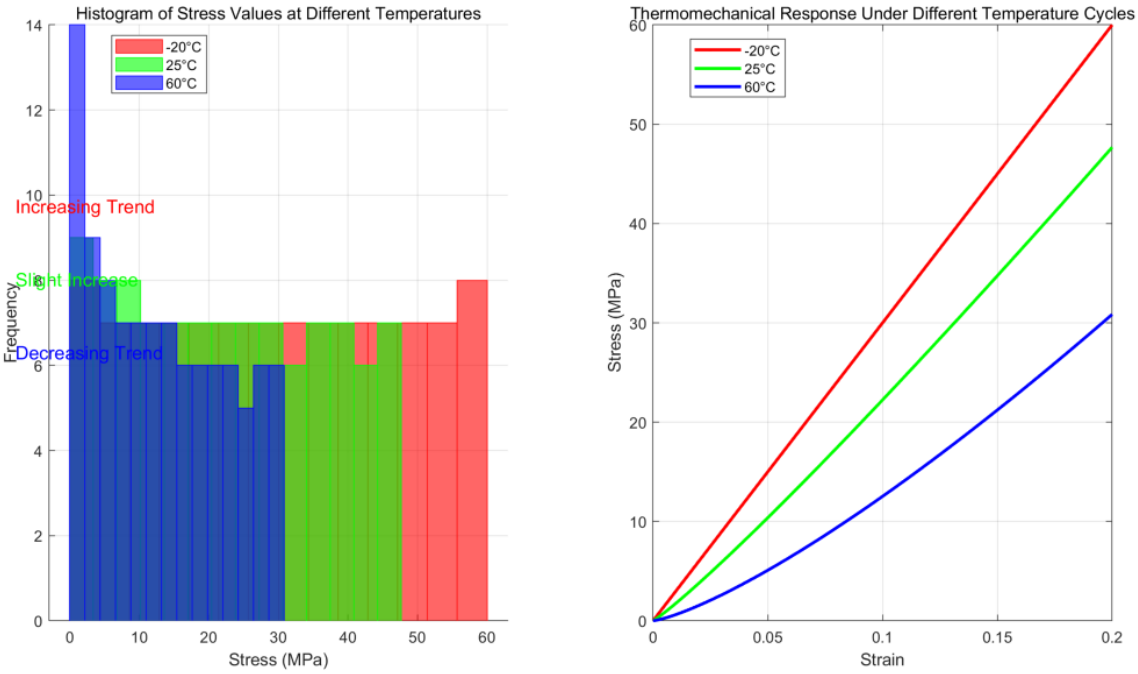

Figure 12. Thermomechanical response and biomechanical optimization model of lithium positive electrode material under different temperature cycles.

The experimental results indicate that temperature cycling significantly affects the mechanical properties of lithium-ion cathode materials. At low temperatures, the material exhibits high rigidity and low ductility, while at high temperatures, the strength and rigidity of the material significantly decrease, indicating the onset of thermal fatigue effects. Through biomechanical optimization models and the adaptive mechanism of biomaterials to temperature changes, the thermal mechanical response of materials was successfully predicted, revealing the expansion and contraction effects of materials caused by temperature. This model provides theoretical guidance for the design and optimization of lithium batteries under extreme temperature conditions.

5. Conclusion

This article proposes a bio-inspired strategy for recycling lithium-ion positive electrode materials, which has been optimized through biomechanical analysis. Experimental results and simulations demonstrate that this method achieves high recycling efficiency and low cost, highlighting the significant potential of bio-inspired approaches in material recycling. Future research should focus on optimizing key parameters such as temperature, chemical catalysts, and time to enhance efficiency and reduce energy consumption. Additionally, exploring the integration of other bio-inspired strategies, such as self-healing materials or bio-based solvents, could further improve the process. Developing scalable techniques for industrial implementation, assessing the long-term environmental impact, and evaluating the economic feasibility of these methods will be crucial for advancing the sustainable development of lithium battery recycling technologies.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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