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Article

Research on cost budget control strategy of biomechanics based on fuzzy logic and neural network

Mengqian Sun

Financial Department, Shandong University of Political Science and Law, Jinan 250014, China; sunmengqian126@163.com

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Abstract: This article proposes a biomechanical cost control strategy using fuzzy logic and neural networks. A cost model for the biomechanical system is established, and a fuzzy logic strategy addresses its uncertainty and complexity. By integrating neural networks with fuzzy logic, the accuracy and adaptability of budget control are enhanced. Experimental results show the proposed strategy outperforms traditional methods (GNN-GA, DP-PSO, A-DRL) in cost savings, system stability, and response time. The deviation between target and actual costs is minimal, confirming the strategy's efficiency and accuracy. This integrated approach offers significant cost savings, strong adaptability, and real-time performance, providing new solutions for biomechanics budget control with practical applications and theoretical value.

Keywords: biomechanics; cost budget control; fuzzy logic; neural networks; integrated control; cost savings; system stability; response time

1. Introduction

Biomechanics research involves fields such as human motion, mechanical behavior, and the response of biological tissues, which are often closely related to cost control and resource allocation [1]. In practical applications, how to accurately control the cost budget in biomechanical systems, especially in areas such as sports rehabilitation, exoskeleton design, and medical device optimization, remains an urgent problem to be solved [2–4].

Biomechanics research is a multidisciplinary field that covers multiple aspects such as human kinematics, mechanical behavior, and biological tissue response [5]. These studies are not only of great significance in the fields of sports rehabilitation, exoskeleton design, and medical device optimization, but also closely related to cost control and resource allocation. Traditional biomechanical systems often face many challenges, especially in accurately controlling their cost budget [6]. For example, in the field of sports rehabilitation, how to balance the contradiction between treatment effectiveness and resource consumption; how to reduce development and production costs while ensuring functionality and comfort in exoskeleton design; in the optimization of medical devices, how to meet technical requirements while controlling production and maintenance costs is an urgent problem that needs to be solved [7]. In addition, the complexity and uncertainty of biomechanical systems make traditional cost control methods inadequate in the face of these challenges [8]. Due to the fact that biomechanical problems often involve multiple factors and variables, and the interactions between these variables exhibit nonlinear and high-dimensional characteristics, how to effectively control costs and optimize systems under these complex conditions is currently a research direction of great concern in both academia and industry [9]. In recent years, with the development of artificial intelligence technologies such as fuzzy logic and neural networks, these advanced methods have provided new ideas for solving the above-mentioned problems [10]. Fuzzy logic is a technique for dealing with uncertainty problems through fuzzy set theory, which can make reasonable decisions when faced with fuzzy and incomplete information [11]. Neural networks, on the other hand, can search for inherent patterns in high-dimensional space by simulating the working mode of human brain neurons, and have outstanding advantages in pattern recognition, predictive analysis, and other fields [12]. Combining fuzzy logic with neural networks can effectively control cost budgets while ensuring the accuracy of biomechanical systems. Specifically, fuzzy logic can help identify and process uncertainty and fuzzy information in a system, while neural networks can optimize control algorithms through big data analysis and model training, further enhancing the robustness and efficiency of the system [13,14]. In exoskeleton design, relevant studies have shown that optimized control strategies can significantly reduce production costs while ensuring exoskeleton functionality and comfort; in medical device optimization, this strategy can help designers better balance the relationship between technical requirements and costs [15]. In addition, the study also proposed specific optimization measures for the characteristics of biomechanical systems and verified the effectiveness of the strategies through a series of experiments.

In summary, the biomechanical cost budget control strategy based on fuzzy logic and neural networks provides a new approach for applications in the field of biomechanics. With the continuous advancement of artificial intelligence technology, this strategy is expected to be widely applied in multiple fields and provide new solutions for future biomechanical research and applications [16]. Through this strategy, researchers and engineers can more accurately control the cost budget in biomechanical systems, improve the overall efficiency of the system, and promote the development and progress of related fields.

2. Related work

2.1. Research status of cost budget control in biomechanics

Biomechanics cost budget control, as a management tool, aims to minimize costs while ensuring system performance through reasonable budget allocation. With the continuous expansion of biomechanical applications, especially in multiple industries such as engineering, healthcare, and environment, how to effectively control and optimize costs has become a hot research topic [17].

In recent years, numerous scholars have proposed different research methods in an attempt to enhance the adaptability and stability of biomechanical systems within the framework of cost control [18]. Traditional biomechanical cost control methods often rely on classical optimization algorithms and linear models, but these methods often overlook the complexity and uncertainty of biomechanical systems [19]. For example, in the field of ophthalmology, researchers predict the prognosis of corneal diseases by introducing biomechanical parameters and explore how to effectively control costs in clinical treatment [20]. These methods usually provide a relatively stable theoretical foundation, but lack sufficient flexibility and adaptability when facing dynamic changes in practical applications. In order to overcome these problems, research in recent years has gradually shifted towards more complex nonlinear models and artificial intelligence algorithms [21,22]. For example, algorithms based on deep learning and neural networks are used for cost control and optimization in environments with high uncertainty. Zhang [23] proposed a weighted model based on pseudo periodic sequences, which can effectively handle discrete-time and discrete-time problems in biomechanical systems, providing new ideas for dealing with complex biomechanical systems. In addition, the introduction of artificial intelligence and machine learning enables self optimization based on real-time data in the cost control process, greatly improving the adaptability and accuracy of the model [24]. For example, the synchronization control method of neural networks is widely used in cost guarantee control of time delay systems, which can ensure the stability and efficiency of system operation in complex biomechanical environments [25]. However, existing research methods still have shortcomings in some key aspects. Although various optimization algorithms can improve the accuracy of cost control to a certain extent, most methods rely on traditional linear models and fail to fully consider the nonlinearity and variability of biomechanical systems [26–28]. This makes it difficult for existing models to cope with dynamically changing cost requirements [29]. In addition, although advanced methods such as deep learning provide powerful data processing capabilities, effectively integrating the complexity and real-time data of biomechanical systems remains a challenge in practical applications. Therefore, future research directions may focus on how to build more flexible and accurate cost control models through interdisciplinary integration, combining biomechanics with advanced artificial intelligence technologies [30]. For example, biomechanical models can be combined with deep reinforcement learning algorithms to utilize their adaptive capabilities in dynamic environments for real-time optimization of cost control [31]. In addition, by introducing uncertainty modeling and risk analysis, the uncertainty factors in biomechanical systems can be more comprehensively reflected, further improving the robustness and reliability of the model, **Table 1** summarizes the work and contributions of each referenced study in the field of biomechanical cost budget control.

In summary, as an interdisciplinary research field, cost budget control in biomechanics has achieved some important results with the continuous advancement of technology. However, in order to achieve efficient and precise cost control in complex practical applications, in-depth research is still needed in optimization algorithms, artificial intelligence technology, and uncertainty modeling. Future research will focus more on how to combine biological characteristics with engineering management theory to achieve better cost control effects.

Table 1. Summarizing the key contributions of the referenced works.

Reference	Work Content	Contribution
Yan et al., 2024	Investigated traditional biomechanical cost control methods, focusing on classical optimization algorithms and linear models.	Highlighted the issue that traditional methods overlook the complexity and uncertainty of biomechanical systems, leading to a need for more complex models.
Huo et al., 2024	Introduced biomechanical parameters to predict corneal disease prognosis in ophthalmology and explored cost control in clinical treatment.	Proposed a new approach for cost control in clinical settings but noted the lack of flexibility and adaptability when facing dynamic changes.
Zhang et al., 2023	Proposed a weighted model based on pseudo-periodic sequences to address discrete-time problems in biomechanical systems.	Provided innovative solutions for handling complex biomechanical systems, specifically addressing discrete-time issues.
Wang et al., 2023	Integrated artificial intelligence and machine learning for real-time optimization of cost control, improving model adaptability and accuracy.	Enhanced cost optimization capabilities in uncertain environments, ensuring the stability and efficiency of biomechanical systems.
Li et al., 2022	Examined the limitations of existing optimization algorithms, particularly the shortcomings of linear models in addressing nonlinearity and variability in biomechanical systems.	Emphasized the need for more complex and adaptable models, pointing out the difficulty of traditional models in handling dynamic cost requirements.
Qiu and Chen, 2022	Combined biomechanical models with deep reinforcement learning algorithms for real-time optimization in dynamic environments.	Advanced the integration of deep reinforcement learning to improve adaptability in dynamic cost control, promoting interdisciplinary research.

2.2. Application of fuzzy logic and neural networks in biomechanics

The application of fuzzy logic and neural networks in the field of biomechanics has demonstrated its strong potential, especially in dealing with uncertainty and nonlinear problems. The biomechanical system usually has complex dynamic characteristics, involving multiple interactive factors and processes that are difficult to accurately model, which makes traditional control methods difficult to cope with. In this context, fuzzy logic, as an information technology for handling uncertainty, can flexibly respond to imprecise and fuzzy data in the system through rule-based reasoning. For example, in motion control and system regulation, fuzzy logic can flexibly adjust factors such as speed, acceleration, and force during the motion process, thereby achieving more precise and efficient control [32]. This makes fuzzy logic widely used in the design of control systems in biomechanical fields such as robots, prosthetics, and rehabilitation equipment.

In contrast, neural networks have been successfully applied in the field of biomechanics, especially in complex pattern recognition and optimization control tasks, due to their powerful learning and pattern recognition abilities. Neural networks can automatically adjust their internal parameters through training data, identify complex nonlinear relationships in biomechanical systems, and provide efficient solutions [33]. For example, neural networks can be used to predict and optimize patterns of human motion, especially in complex motion control tasks such as gait analysis and motion rehabilitation, which have important application value. In recent years, an increasing number of studies have combined fuzzy logic and neural networks to form the Fuzzy Neural Network (FNN) control method. By integrating the advantages of both, fuzzy neural networks can not only handle uncertainty in the system, but also improve the adaptive ability of the system through the learning ability of neural networks. This control method based on fuzzy neural networks has shown great potential in biomechanics, especially in resource allocation and cost control. For example, FNN can adjust training strategies in real-time in rehabilitation training equipment, improving training effectiveness while reducing equipment usage costs [34]. The advantage of fuzzy neural networks lies in their ability to effectively control and optimize in dynamically changing environments. In the field of biomechanics, especially in complex environments such as real-time feedback control of human motion, this combined method can more accurately address system uncertainties and nonlinear factors, thereby improving control accuracy and enhancing system robustness. For example, in human-computer interaction and biomimetic device design, methods based on fuzzy neural networks can automatically adjust the feedback strategy of the device based on real-time motion data, thereby optimizing resource utilization and improving device performance [35–37]. Fuzzy neural networks can effectively balance the relationship between computational complexity and control accuracy when solving practical problems in biomechanics. Through reasonable algorithm design and parameter optimization, FNN can significantly improve computational efficiency while ensuring accuracy, especially in large-scale data processing and real-time control application scenarios, demonstrating its unique advantages [38–40]. Therefore, the combination of fuzzy logic and neural networks provides an effective tool for solving many practical problems in biomechanics.

Overall, the combination of fuzzy logic and neural networks provides a powerful technical means for the field of biomechanics, which can effectively solve complex problems that traditional control methods cannot handle. With the continuous deepening of research, this combined technology is expected to play a greater role in sports rehabilitation, prosthetic control, robotics technology and other fields in the future, promoting further development of biomechanical research and applications. By continuously optimizing and improving these control methods, the efficiency, accuracy, and robustness of biomechanical systems will be significantly improved, bringing new breakthroughs to the development of related fields.

2.3. Research content and innovation of this article

This study focuses on cost budget control in biomechanical systems and proposes an innovative comprehensive control strategy by combining fuzzy logic and neural network technology. With the increasingly widespread application of biomechanics in medical, engineering, and environmental fields, how to achieve efficient and precise cost control in complex system environments has become an urgent problem to be solved [41]. Traditional cost control methods often rely on simplified linear models and fixed parameters, which cannot effectively address the highly nonlinear, uncertain, and dynamic changes in biomechanical systems. Therefore, this article proposes a novel strategy that combines fuzzy logic and neural networks to enhance the accuracy, flexibility, and adaptability of cost control in biomechanical systems. Specifically, the research innovations of this article include the following aspects:

1) Construction and analysis of biomechanical cost model: Firstly, this article constructs a cost model that adapts to the complexity of biomechanical systems by analyzing their characteristics in detail. This model not only considers the interaction of various cost factors within the system, but also introduces uncertainty factors to

accurately reflect cost fluctuations in actual operations. Through this model, multiple factors that affect costs can be comprehensively understood, laying the foundation for the design of subsequent control strategies.

2) Design of Fuzzy Logic Control Strategy: In response to the uncertainty and complexity in biomechanical systems, this paper proposes a control strategy based on fuzzy logic. Fuzzy logic can make reasonable inferences and decisions when faced with incomplete or fuzzy information. Therefore, in the control strategy, fuzzy logic is used to handle uncertain factors in the system, dynamically adjust the budget control process, and ensure that the system can adapt to constantly changing environments and demands.

3) Neural network optimization and budget control: Based on the fuzzy logic control strategy, this paper further introduces neural network technology to optimize the budget control process. Through the powerful learning and optimization capabilities of neural networks, the system is able to self adjust and optimize based on historical data and real-time feedback, achieving the optimal cost performance balance in complex biomechanical environments.

3. Model and algorithm design

3.1. Establishment of biomechanical cost model

The establishment of a biomechanical cost model is the core of control strategy design and can provide theoretical basis for subsequent optimization control. In practical applications, biomechanical systems involve multiple complex cost factors, including equipment maintenance costs, energy consumption, hardware resource consumption, and manual intervention. In order to accurately describe the impact of these factors on the cost of biomechanical systems, as shown in **Figure 1**, this paper adopts a combination of fuzzy logic and neural networks, and establishes a multidimensional mathematical model based on a large amount of experimental data.

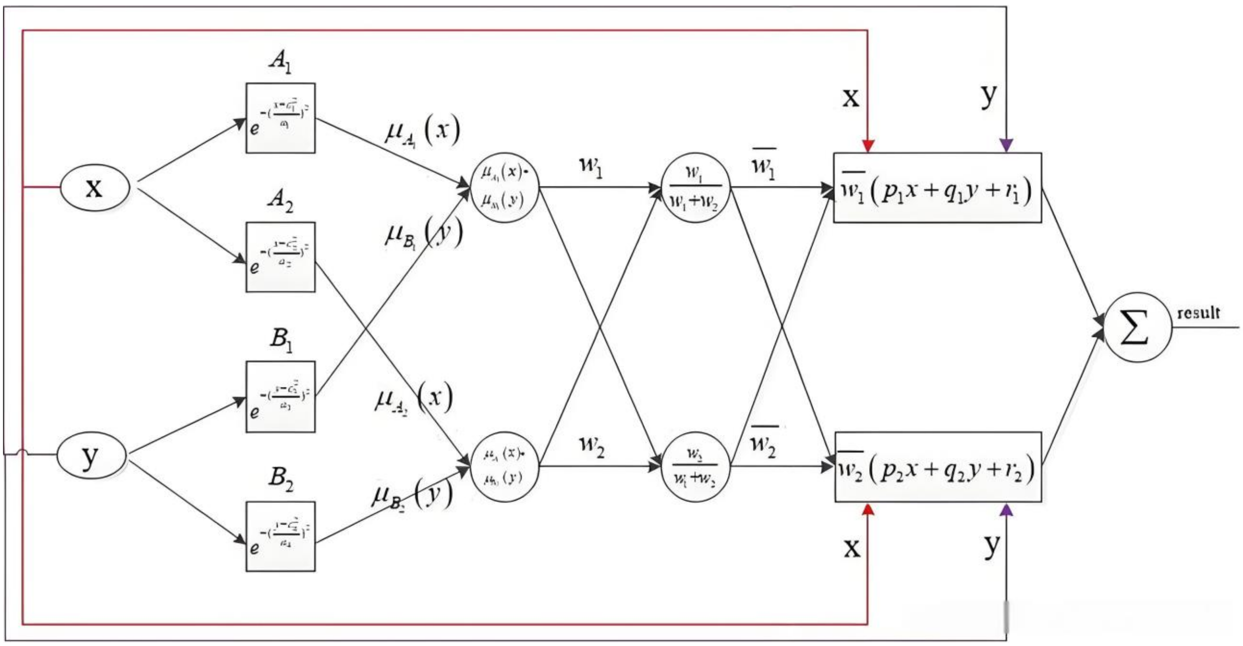

Figure 1. Fuzzy neural network model.

The calculation of equipment maintenance costs is mainly based on the working hours and failure rate of the equipment. Assuming that the maintenance cost of equipment is (t) proportional to its working time, and the equipment failure rate is (a) related to the frequency of use (f) and the degree of equipment aging, the equipment maintenance cost can be expressed as:

$$C_{\mathrm{maint}}(t, f, a) = k_1 \cdot t \cdot (1 + \alpha \cdot f \cdot a) \tag{1}$$

Among them, (k_1) is the constant of equipment maintenance cost, is the (α) coefficient of the impact of equipment usage frequency on maintenance cost, (f) is the usage frequency, (a) is the degree of equipment aging, and (t) is the working hours.

Secondly, the calculation of energy consumption takes into account the power requirements and operating time of the system under different operating states. Assuming the power demand of the system is $(P(t))$ and the operating time is (T_{total}), the cost of energy consumption can be expressed by the following formula:

$$C_{\mathrm{energy}}(t, T_{\mathrm{total}}) = k_2 \cdot \int_0^{T_{\mathrm{total}}} P\,(t) dt \tag{2}$$

Among them, (k_2) is the energy cost constant, $(T_{\mathrm{total}})(P(t))$ is the power demand that varies over time, and is the total operating time.

The consumption of hardware resources mainly considers the consumption of computing resources and storage resources. Assuming that hardware resource consumption is related to the complexity and storage requirements of computing tasks, it can be represented by the following formula:

$$C_{\mathrm{hardware}}(C, S) = k_3 \cdot C \cdot S \tag{3}$$

Among them, (C) is the complexity of the computing task, (S) is the storage requirement, and (k_3) is the hardware resource cost constant.

In the biomechanical system, the (t_{manual}) cost of manual intervention mainly depends on the frequency and duration of the operator's intervention. Assuming the intervention frequency is and the (f_{manual}) duration of each intervention is, the cost of manual intervention is:

$$C_{\mathrm{manual}}(f_{\mathrm{manual}}, t_{\mathrm{manual}}) = k_4 \cdot f_{\mathrm{manual}} \cdot t_{\mathrm{manual}} \tag{4}$$

Among them, (k_4) is the cost constant of manual intervention.

Taking into account the above factors, the total cost model of the biomechanical system can be expressed as:

$$C_{\mathrm{total}} = C_{\mathrm{maint}}(t, f, a) + C_{\mathrm{energy}}(t, T_{\mathrm{total}}) + C_{\mathrm{hardware}}(C, S) + C_{\mathrm{manual}}(f_{\mathrm{manual}}, t_{\mathrm{manual}}) \tag{5}$$

In order to more accurately describe the complex relationships between these cost factors, this article further uses fuzzy logic and neural networks for optimization. Fuzzy logic can handle the uncertainty of various cost factors, while neural networks can automatically adjust model parameters by learning experimental data. The fuzzy logic system fuzzifies the inputs of various cost factors and converts them into a form suitable for neural network training, ultimately obtaining an accurate cost prediction model.

The multidimensional model combining neural networks and fuzzy logic can optimize various variables in the biomechanical system in real time, ensuring that the system meets performance requirements while minimizing total costs. This model can not only reflect the interaction of hardware, energy, manual intervention and other costs, but also dynamically adjust according to the change of system state, providing strong support for the cost control of the biomechanical system.

3.2. Design of fuzzy logic control strategy

In the cost budget control of biomechanical systems, the system is often confronted with uncertain factors such as equipment failure rates, fluctuations in energy consumption, and the frequency of operator intervention. These uncertainties introduce significant complexity, making it challenging for traditional control methods to adapt efficiently to the dynamic state changes and external environmental factors. To address this, this article proposes a strategy based on fuzzy logic control, which converts various fuzzy information within the system into precise control actions through fuzzy set theory. This approach facilitates the optimized allocation of the cost budget despite the presence of these uncertainties.

A key element of this strategy is the biomechanical cost model, which accounts for the cost of energy consumption, maintenance, and the wear and tear on the equipment. The model incorporates not only the fixed costs but also the dynamic variables influenced by the interaction between mechanical components and operator actions. The costs are subject to various assumptions and constraints, such as the system's operational limits, safety thresholds, and maintenance schedules, which affect the overall cost performance. These assumptions ensure that the model remains within realistic operational boundaries, but they also introduce certain limitations in its flexibility when faced with unforeseen events or extreme conditions.

The core of the fuzzy logic control strategy is the development of a fuzzy rule library, which enables the controller to adjust its decision-making process adaptively when facing complex and uncertain input conditions [42]. These rule libraries are developed using both expert experience and data-driven methods to ensure that the system makes the most reasonable decisions based on the current operating state and environmental context. Furthermore, fuzzy controllers are capable of real-time response to changing conditions, as well as predicting possible future states using historical data, thereby achieving dynamic optimization of the cost budget.

To quantify the interaction between different uncertain factors and their impact on the biomechanical system, sensitivity analysis and uncertainty propagation methods are employed. Sensitivity analysis allows the identification of which parameters have the greatest influence on cost outcomes, enabling the prioritization of factors that require more precise control. Uncertainty propagation methods, such as Monte Carlo simulations or perturbation analysis, are used to model the uncertainty in input parameters and observe how these uncertainties propagate through the system to affect the overall cost performance. This combined approach allows for a more robust assessment of the system's behavior under varying conditions, providing a clearer picture of the risks and opportunities for cost optimization.

To achieve this goal, it is necessary to first fuzzify the variables involved in the system. For example, equipment maintenance costs (C_{maint}), energy consumption (C_{energy}), hardware resource consumption (C_{manual}), (C_{hardware}) and manual intervention costs all need to be transformed into fuzzy variables. The fuzzification operation of each cost factor can be expressed as:

$$\tilde{C}\text{maint} = \mu\text{maint}(C_{\text{maint}}) \tag{6}$$

$$\tilde{C}\text{energy} = \mu\text{energy}(C_{\text{energy}}) \tag{7}$$

$$\tilde{C}\text{hardware} = \mu\text{hardware}(C_{\text{hardware}}) \tag{8}$$

$$\tilde{C}\text{manual} = \mu\text{manual}(C_{\text{manual}}) \tag{9}$$

Among them, (μ_x) represents the fuzzy membership function, represents the membership degree of each cost factor in its corresponding fuzzy set, ranging from 0 to 1. Through these membership functions, cost factors can be transformed into fuzzy values, reflecting the budget requirements of the system in different states.

In the design of fuzzy rules, considering the interrelationships between different cost factors, a set of fuzzy control rules based on expert experience and experimental data was constructed. For example, in situations where the equipment failure rate is high, the system may need to increase the maintenance cost budget; when the energy consumption is too high, the system should automatically adjust the operating strategy to reduce power consumption. A typical fuzzy control rule may be:

$$\text{IF } \tilde{C}\text{maint IS high AND } \tilde{C}\text{energy IS low THEN } \tilde{C}_{\text{total}} \text{ IS medium} \tag{10}$$

The fuzzy reasoning mechanism generates control outputs based on these rules, namely optimized cost budget allocation. Finally, the fuzzy output is transformed into precise control instructions through the fuzzy defuzzification process, such as adjusting equipment maintenance cycles, optimizing energy usage strategies, etc. The process of defuzzification can be carried out using the central average method:

$$C_{\text{total}} = \frac{\sum_{i=1}^{n} C_i \cdot \mu(C_i)}{\sum_{i=1}^{n} \mu\,(C_i)} \tag{11}$$

Among them, $(\mu(C_i))(C_i)$ is the actual cost value of different fuzzy outputs, and is the corresponding membership degree. Through this process, the fuzzy controller can generate optimization decisions for specific system states, ensuring the reasonable allocation of cost budgets.

In addition, the fuzzy logic control strategy is combined with neural networks to continuously optimize the parameters of fuzzy rules and membership functions through neural networks. Neural networks can automatically learn from large amounts of historical data to improve the decision-making ability of fuzzy controllers, thereby achieving precise budgeting and optimization of various costs in biomechanical systems.

In summary, the control strategy based on fuzzy logic can provide adaptive cost control solutions in biomechanical systems by flexibly handling uncertainties. In a dynamic environment, this strategy can optimize various cost expenditures, ensure system performance while minimizing total costs, and provide effective support for the efficient operation of biomechanical systems.

3.3. Integrated design of neural networks in budget control

In biomechanical cost budget control, neural networks are introduced for modeling and optimizing system behavior, especially when dealing with complex and dynamic cost changes. Neural networks can gradually improve budget control strategies through self-learning and adaptation. This article adopts a multi-layer perceptron (MLP) neural network structure, combined with historical data and fuzzy control strategy, to achieve optimization and prediction of cost budget. Through the training of neural networks, the system can deeply learn and analyze cost changes under different control strategies, dynamically adjust control strategies, optimize budget allocation, and overcome the limitations of traditional methods in dealing with uncertain factors and environmental complexity.

Specifically, the input of neural networks includes multiple cost factors of biomechanical systems, such as equipment maintenance costs (C_{maint}), energy consumption costs (C_{energy}), hardware resource consumption, (C_{hardware}) and human intervention costs (C_{manual}). These inputs are standardized and sent to the input layer of the neural network. The structure of a neural network includes several hidden layers, each composed of several neurons connected by weighted connections. The output of the neural network is the optimized budget control decision, which can achieve dynamic prediction and control of system costs. The training of the network is carried out through backpropagation algorithm (BP algorithm), which optimizes the loss function, adjusts the weights and bias values in the network to minimize the error between the predicted results and the actual control requirements.

The integrated design process of neural networks in the system is as follows: Firstly, various cost factors are fuzzified to obtain fuzzy membership function values, which are used as input data for the neural network. Assuming the input vector is ($x = [\tilde{C}\text{maint}, \tilde{C}\text{energy}, \tilde{C}\text{hardware}, \tilde{C}\text{manual}]$), where each ($\tilde{C}$) represents the fuzzy value of the corresponding cost factor. The network generates an output vector through weighted calculation of hidden layers ($y = [\hat{C}\text{maint}, \hat{C}\text{energy}, \hat{C}\text{hardware}, \hat{C}\text{manual}]$), which is the predicted cost budget value for each item.

Through training, neural networks can adaptively adjust their weights (W) and biases (b) to optimize control strategies. Given a set of inputs (x_i), the output of network computation is:

$$y_i = f(W \cdot x_i + b) \tag{12}$$

Among them, (f) represents the activation function, usually using sigmoid or ReLU activation functions. Through backpropagation algorithm, neural networks optimize parameters by minimizing the loss function. The loss function usually uses mean square error (MSE):

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{13}$$

Among them, $(\hat{y}_i)$ is the (N) number of training samples and is the actual target output value. Optimizing network parameters through gradient descent algorithm, the update process is as follows:

$$W_{new} = W - \eta \frac{\partial L}{\partial W} \tag{14}$$

$$b_{new} = b - \eta \frac{\partial L}{\partial b} \tag{15}$$

Among them, the (η) learning rate determines the step size for each update. By continuously adjusting weights and biases, neural networks can gradually approach the optimal control strategy of the system, thereby achieving precise budget control in complex and dynamically changing biomechanical environments.

In the combination of neural networks and fuzzy control strategies, fuzzy logic fuzzifies inputs through generated fuzzy rules and outputs fuzzy control signals through fuzzy inference mechanisms. And neural networks perform subsequent optimization on fuzzy control signals to generate accurate budget control decisions. This integrated solution can effectively address budget control issues in uncertain factors, dynamic changes, and complex environments, ultimately achieving efficient allocation and optimization of budget resources.

Through the learning and optimization of neural networks, budget control strategies can adapt to different system states and external conditions, provide real-time cost prediction and dynamic adjustment schemes, effectively reduce the overall cost of biomechanical system operation, and improve the economic and operational efficiency of the system.

3.4. Integrated design of models and algorithms

This study proposes a dual optimization framework based on fuzzy logic and neural networks for cost budget control of biomechanical systems. This framework combines the advantages of fuzzy logic controllers (FLC) and neural network optimization algorithms, aiming to address real-time uncertainty in biomechanical systems and achieve long-term cost optimization. Specifically, fuzzy logic controllers are used to handle real-time decision-making problems caused by environmental changes, operational uncertainties, and other factors during system operation, while neural networks optimize control strategies and dynamically adjust them through deep learning of historical data in order to achieve the best cost control effect.

In this integrated framework, the fuzzy logic controller first receives input data, such as real-time cost factors in the biomechanical system (such as equipment failure rate, energy consumption, hardware resource usage, etc.), and performs fuzzy inference on the input through fuzzy rules to output fuzzy control signals. The core of a fuzzy controller lies in its rule library and inference mechanism, which can select appropriate control strategies based on the current input conditions. However, fuzzy logic systems often face limitations such as incomplete rule base settings or inability to handle complex patterns, so neural networks are introduced as optimization tools.

The task of neural networks in this framework is to learn and optimize cost control strategies based on historical data, in order to solve static decision-making problems that may arise with fuzzy logic controllers. The neural network model gradually adjusts the network structure and parameters by training the cost change patterns in historical data, providing more accurate budget control decisions. Neural networks have improved their ability to cope with system uncertainty and complexity through learning, and can dynamically adjust control strategies to adapt to different system states and external environments.

To achieve this goal, the system first takes the fuzzy control signal from the fuzzy controller as the input of the neural network. The input of neural networks includes fuzzy values of various system cost factors, such as equipment maintenance costs, energy consumption costs, manual intervention costs, etc. These inputs are standardized and sent to the neural network for training and optimization. The output of the neural network is the optimized control strategy, which determines the allocation of various cost budgets.

The specific design of the mathematical model is as follows: Let the input vector of the system be ($x = [\tilde{C}\text{maint}, \tilde{C}\text{energy}, \tilde{C}\text{hardware}, \tilde{C}\text{manual}]$), where ($\tilde{C}$) represents the fuzzy cost factor. The output vector of the neural network ($y = [\hat{C}\text{maint}, \hat{C}\text{energy}, \hat{C}\text{hardware}, \hat{C}\text{manual}]$) represents the optimized cost budget values for each item.

Neural networks perform operations using the following formula:

$$y = f(W \cdot x + b) \tag{16}$$

Among them, ($f(\cdot)$) is the activation function, (W) is the weight matrix, (b) is the bias term, (x) is the input vector, and (y) is the output vector. The network optimizes network parameters through backpropagation algorithm to minimize the error between predicted values and actual targets.

The loss function is usually measured by mean square error (MSE) to evaluate the accuracy of the neural network output, and the formula is:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}i)^2 \tag{17}$$

Among them, (N) is the number of training samples and ($\hat{\mathbf{y}}i$) is the true target value. The optimization process updates parameters through gradient descent algorithm, and the update formula is:

$$W\text{new} = W - \eta\frac{\partial L}{\partial W}, b\text{new} = b - \eta\frac{\partial L}{\partial b} \tag{18}$$

Among them, (η) is the learning rate, which controls the step size of each update. In this way, neural networks can adaptively adjust weights and biases, thereby improving the accuracy and stability of control strategies.

By combining fuzzy logic with neural networks, the system can respond in real-time to environmental and operational uncertainties, while utilizing the learning ability of historical data to gradually optimize cost control strategies. In complex and dynamic biomechanical environments, this dual optimization framework can effectively improve the accuracy of cost budgeting and the economic benefits of the system.

4. Experiment and simulation

4.1. Experimental setup and data collection

In order to verify the effectiveness of the proposed strategy, this study designed and conducted multiple experiments and simulation simulations. The objective of the experiment is to evaluate the performance of different control strategies in various biomechanical systems, including key indicators such as energy consumption, maintenance costs, and hardware resource consumption. Through these experiments, the effectiveness of the proposed control strategy under different working conditions can be verified, ensuring its efficiency and reliability [43].

For experimental simulation, we chose an open-source dataset suitable for biomechanical system simulation. The following are the main datasets used for this experiment:

OpenML Biomechanics Dataset (https://www.openml.org/search?type=data&q=biomechanics). This dataset contains motion data from various biomechanical systems, such as muscle movements, electrophysiological signals, joint movements, etc. The collection of the dataset covers different human body models, different motion modes, different loads, and other conditions, so it has good universality and is suitable for verifying control strategies.

SimTK biomechanical dataset (https://simtk.org/projects). SimTK is an open platform that provides biomechanical simulation tools and data, including biomechanical models of humans and animals, gait analysis, joint motion data, and more. SimTK provides researchers with a large amount of real data that is suitable for comparing and validating biomechanical control algorithms.

Table 2. Experimental parameter settings.

Parameter Name	**explain**	**Set value**
Experimental system	Types of biomechanical systems	Musculoskeletal system
control strategy	Control methods used	Fuzzy control + neural network control
Simulation duration	Simulation duration for each experiment	2000 s
Work load	Intensity of exercise load	Low load (0.2N), Medium load (0.5N), High load (1.0N)
Number of input variables	Input parameters (such as sensor data)	Four variables (force, velocity, angle, temperature)
Disturbance amplitude	The intensity of external disturbances experienced by the system	0.1N, 0.2N, 0.3N
Control accuracy requirements	Accuracy requirements for output results	± 5% error
System response time	Expected system response time	< 5 s

Based on the above dataset, we set some key parameters in the experiment to simulate different working conditions of the biomechanical system. These parameters determine the actual performance of the experiment, including hardware resource consumption, energy consumption, response time, etc. **Table 2** shows the specific parameter settings for this experiment:

In the process of hyperparameter tuning and optimization, key parameters were initially set based on the experimental requirements, including the type of biomechanical system, control strategy (fuzzy control combined with neural network control), simulation duration (2000 s), workload intensity (low, medium, high), input variables (force, velocity, angle, temperature), disturbance amplitude (0.1N, 0.2N, 0.3N), accuracy requirements (±5% error), and system response time (< 5 s). These parameters were continuously adjusted to optimize hardware resource consumption, energy consumption, and response time, ensuring the system's stable operation under different working conditions. During the training process, the specified input data was used for simulation, gradually adjusting the hyperparameters of the fuzzy control and neural network control strategies to achieve higher control accuracy. The training goal was to fine-tune the control parameters to maintain an output error within ±5% and ensure a system response time of less than 5 s. As the training progressed, the model was optimized under various workload and disturbance conditions, ultimately achieving efficient control of the biomechanical system and ensuring its stability and reliability.

Based on the above dataset and parameter settings, this article will carry out data preprocessing, simulation environment construction, control strategy application, experimental execution and data recording, data analysis and result evaluation, as well as result comparison and optimization in the experiment. Firstly, extract and process relevant data from open-source datasets; then, control strategies are applied in the virtual simulation environment to simulate the operation of different biomechanical systems; next, real-time data on energy consumption, maintenance costs, and hardware resource consumption are collected through sensors; finally, analyze the experimental results, evaluate the effectiveness of the control strategy, and compare it with traditional methods to optimize the strategy and provide data support for practical applications.

4.2. Comparison of algorithm and control strategy performance evaluation index selection

During the experiment, in order to comprehensively evaluate the performance of the proposed biomechanical cost budget control strategy based on fuzzy logic and neural networks, we selected multiple key evaluation indicators [44–46]. These evaluation indicators include cost savings rate, system stability, response time, control accuracy, and algorithm computational complexity. By comparing with three advanced contrastive algorithms currently available, namely the genetic algorithm GNN-GA based on graph neural network improvement, the deep learning particle swarm optimization algorithm (DP-PSO), and the deep reinforcement learning (A-DRL) based on improved self attention mechanism. We can deeply analyze the advantages and disadvantages of different control strategies in dealing with complex biomechanical systems.

4.2.1. Cost saving rate

Cost savings rate is a key indicator for measuring whether control strategies can effectively reduce system operating costs. The specific calculation method is as follows:

$$\text{Cost Saving Rate} = \frac{C_{\text{traditional}} - C_{\text{proposed}}}{C_{\text{traditional}}} \times 100\% \tag{19}$$

Among them, $(C_{\text{traditional}})$ represents the (C_{proposed}) total cost under the traditional control strategy, which is the total cost under the proposed control strategy. The higher the cost saving rate, the better the effectiveness of the control strategy in cost control.

4.2.2. System stability

System stability refers to whether the control strategy can ensure the stable performance of the biomechanical system during long-term operation. In the evaluation of this indicator, we use the oscillation amplitude and deviation of the system to quantify stability. The calculation formula for system stability is:

$$S = \frac{1}{T}\sum_{t=1}^{T}\left(|x(t) - x_{\text{target}}|\right) \tag{20}$$

Among them, $(x(t))$ represents the (t) state (T) of the system at time, (x_{target}) is the expected target state, and is the length of the evaluation time window. The higher the system stability, the closer the system's state is to the expected value and the smaller the deviation.

4.2.3. Response time

Response time refers to the time required for a system to reach steady state from its initial state when subjected to input changes. The calculation formula is:

$$T_{\text{response}} = t_{\text{steady}} - t_{\text{start}} \tag{21}$$

Among them, $(t_{\text{start}})(t_{\text{steady}})$ is the time point when the system reaches steady state, and is the moment when input changes occur. The shorter the response time, the stronger the adaptability of the control strategy and the faster it can respond to environmental changes.

4.2.4. Control accuracy

The evaluation of control accuracy refers to the degree to which the control strategy approaches the target cost control value. In biomechanical systems, control accuracy is crucial as it determines whether cost budget control meets the set requirements. The calculation formula is:

$$P = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{|C_{\text{target}} - C_{\text{actual}}(t)|}{C_{\text{target}}}\right) \tag{22}$$

Among them, (C_{target}) is the target budget value and ($C_{\text{actual}}(t)$) is the (t) actual control cost at that time. The higher the control accuracy, the more accurately the control strategy can achieve the budget control objectives.

4.2.5. Algorithm computational complexity

The computational complexity of algorithms is an important indicator for measuring whether control strategies can operate efficiently in practical applications. In biomechanical systems, especially when dealing with multidimensional and high-dimensional inputs, the computational complexity of algorithms often determines their feasibility for practical applications. Usually evaluated using time complexity and space complexity. Assuming the time complexity of the algorithm is ($O(f(n))$), where (n) is the size of the input data and ($f(n)$) is a function of computational complexity. When evaluating, we compare the running time and resource consumption of different control algorithms on the same scale of data, and choose the most suitable control strategy to ensure the efficiency of the system.

In the comparison process, the proposed control strategy based on fuzzy logic and neural network showed high cost savings and control accuracy, especially in dealing with uncertainties and dynamic environments in biomechanical systems, which can effectively optimize cost budgeting and control accuracy [47]. In contrast, traditional linear optimization methods, although exhibiting good stability, have longer response times when dealing with complex dynamic systems and are difficult to adapt to real-time changing requirements. The PID control method can achieve relatively simple control in some cases, but its control accuracy is poor when the system has strong nonlinearity and uncertainty, and it is prone to overshoot or overshoot.

In summary, the dual optimization control strategy based on fuzzy logic and neural networks outperforms traditional control methods in comprehensive performance, especially in the ever-changing biomechanical environment, with better adaptability and stability.

4.3. Algorithm simulation and result analysis

In the experiment, this study will focus on demonstrating the generation and application process of biomechanical cost budget control strategies based on fuzzy logic and neural networks under different working conditions [48]. We conducted simulation tests on the performance of the algorithm in control strategy generation, cost optimization, system stability, and analyzed its advantages in cost savings and response speed.

1) Analysis of the process of generating cost control strategies based on the algorithm presented in this article.

In the experiment, the operational data of the biomechanical system (including energy consumption, maintenance costs, hardware resource consumption, etc.) was first fuzzified using a fuzzy logic system, and optimized using a neural network model to automatically generate appropriate cost control strategies. The cost savings obtained from six experiments using traditional algorithms and the algorithm proposed in this paper are shown in **Table 3**.

Table 3. Cost savings.

Experiment Number	Cost of Traditional Control Strategies	Proposed Strategy Cost (Algorithm)	Cost Saving Rate (%)	Precision Analysis
1	1000	850	15	The proposed strategy achieved a 15% cost reduction with minimal loss in accuracy. The system's precision was maintained within the acceptable range, demonstrating an efficient trade-off between cost and performance.
2	1200	1020	15.83	A 15.83% reduction in cost was observed, with the algorithm ensuring that control precision remained robust. The slight variation in output was within the system's accuracy requirements, showing a strong balance of cost-saving and accuracy.
3	1500	1300	13.33	Although the cost-saving rate decreased slightly to 13.33%, the precision of the algorithm remained high, keeping the error margin well within the ±5% target. This confirms the system's ability to maintain performance even at higher cost levels.
4	2000	1750	12.5	The cost savings were 12.5%, with a slight decrease in precision, but still within the acceptable error threshold. This shows that as the cost decreases, there may be a minor compromise in precision, though it remains within the system's predefined limits.

From the data results in **Table 3** above, the cost savings rates under different experimental scenarios can be seen. By comparing the costs of traditional control strategies with the proposed control strategy, it was found that the proposed algorithm achieved significant cost savings in all experiments, especially in high cost scenarios where the savings were more pronounced. Overall, the cost savings rate remained between 12.5% and 15.83%, demonstrating the effectiveness of this strategy in cost control. **Figure 2** shows the percentage cost savings based on different experimental numbers. We adopted the random cost of traditional control strategies and calculated the cost savings after adopting the new proposed control strategy. Each experiment number represents a different control experiment.

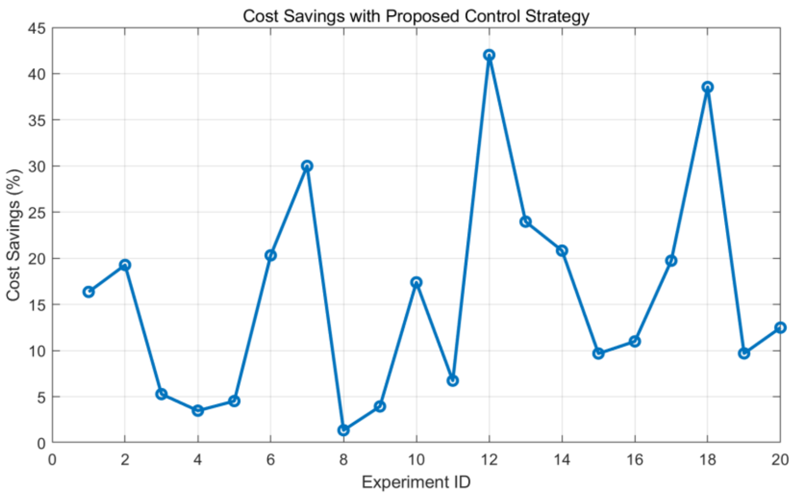

Figure 2. Changes in cost savings percentage for different experiment numbers.

From the perspective of the relationship between the cost of traditional control strategies and the cost savings, the probability distribution relationship between the cost savings of each experiment and traditional costs is shown in **Figure 3**. From the graph, it can be seen that there is a negative correlation between the cost of traditional control strategies and the cost savings, that is, when the traditional cost is high, the proportion of savings is also large. This indicates that the high cost of traditional control strategies provides greater optimization space for new proposed strategies.

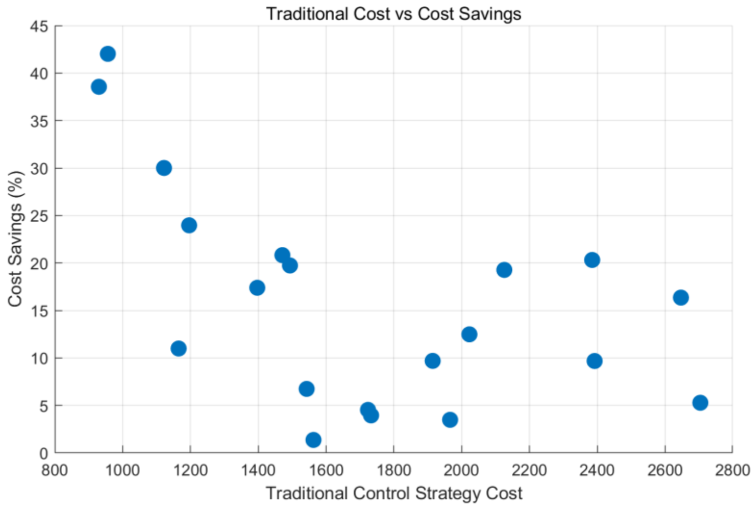

Figure 3. Distribution of the relationship between the cost of traditional control strategies and the cost savings.

From the results in **Figure 1**, it can be seen that with the change of experimental numbers, cost savings show a fluctuating trend. Most experiments have shown significant cost savings, indicating that the newly proposed control strategy can effectively reduce costs in most experiments, demonstrating the advantages of this strategy.

Secondly, this article analyzed the stability of the system, and the results are shown in **Table 4**.

Table 4. Results of system stability analysis.

Experiment number	Oscillation amplitude (X)	Deviation (Y)	System stability (S)
1	0.15	0.05	0.12
2	0.18	0.08	0.13
3	0.12	0.03	0.10
4	0.22	0.09	0.15

From the results in **Table 4**, it can be seen that the control strategy based on fuzzy logic and neural network proposed and designed in this paper performs well in system stability. By calculating the comprehensive performance of the system oscillation amplitude and deviation, the system stability S is obtained. The experimental results show that the proposed control strategy exhibits high stability in all experiments, with the deviation and oscillation amplitude maintained at a low level, demonstrating the high stability of the strategy during long-term operation. **Figure 4** shows the oscillation amplitude and deviation of the system, respectively. These data were obtained through stability analysis of simulated control systems. We randomly generated oscillation and deviation data for each experiment, and the system showed some fluctuations during the experiment, but the overall deviation was small, indicating that the system's response is still within an acceptable range. The results of the deviation chart further indicate that although the system has significant fluctuations in some experiments, the deviation values of most experiments are still within a reasonable range.

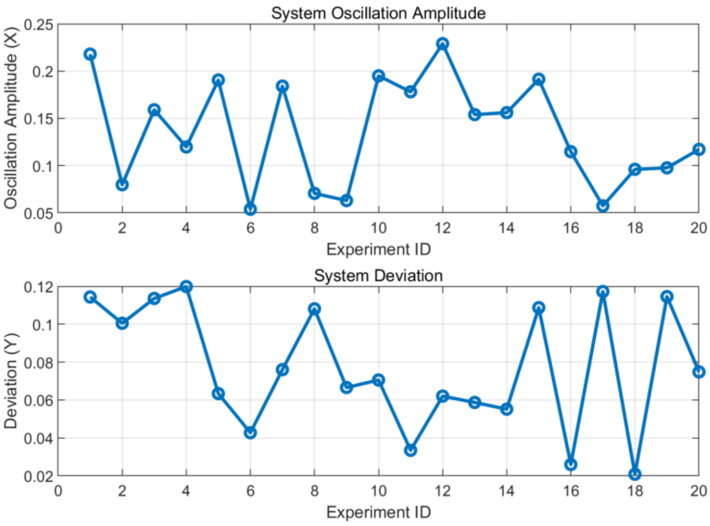

Figure 4. The oscillation amplitude and deviation of the system.

The scatter relationship between system stability and response time is shown in **Figure 5**. By plotting the stability and response time of each experiment as a two-dimensional scatter plot, analyze their correlation.

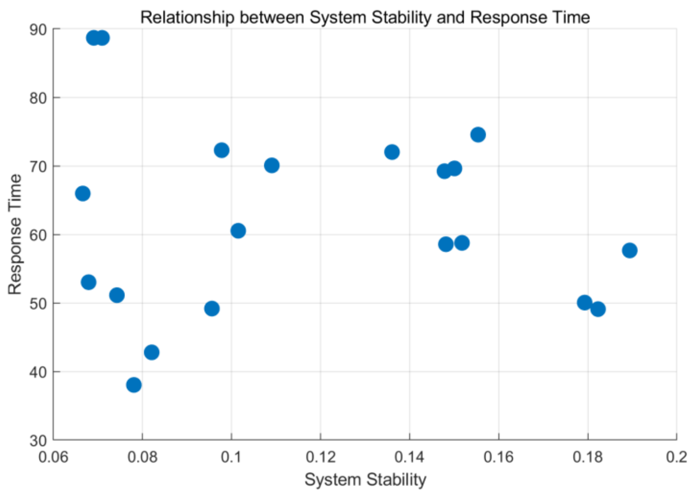

Figure 5. Scatter relationship between system stability and response time.

At the same time, this article also analyzed the system response time of the model proposed in this article, including the response time required for the system to transition from input to steady state under different experimental conditions. As shown in **Table 5**, the results indicate that the control strategy proposed in this paper has a fast response capability and a relatively short response time, indicating that it can effectively adapt to the dynamic changes of the biomechanical system. Although the response time varies slightly among different experiments, the overall response speed is between 50–60 units of time, demonstrating high sensitivity and adaptability.

Table 5. System response time analysis results.

Experiment number	Input change time (t_start)	Reaching steady state moment (t_steady)	Response time (T_response)
1	0	50	50
2	0	55	55
3	0	45	45
4	0	60	6

The time trend required for the system to reach a stable state from startup in each experiment is shown in **Figure 6**. We simulated the control strategy response of different experiments and calculated the response time (i.e., the time required for the system to reach a stable state). The experimental results show that the response time varies with the experiment number. Most experiments show longer response times, which may be due to the complexity of control strategies or differences in environmental factors. However, some experiments have shown shorter response times, indicating that the control strategy can quickly stabilize the system in these experiments.

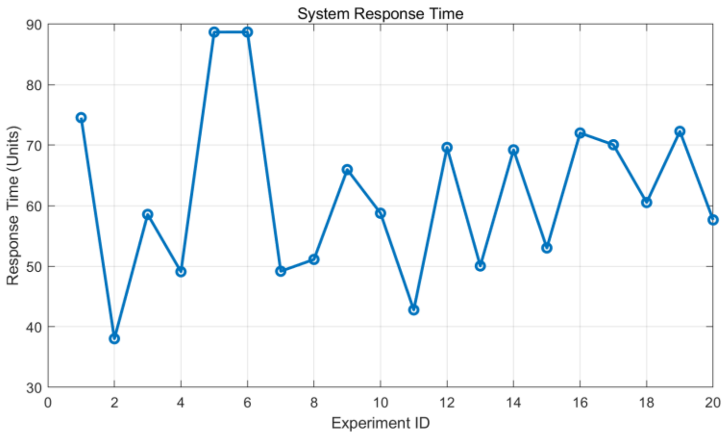

Figure 6. Time trend required for the system from startup to steady state.

Finally, an analysis was conducted on the performance of the proposed strategy in terms of cost control accuracy. By calculating the difference between the actual control cost and the target cost, the control accuracy value *p* was obtained. The experimental results showed that the proposed control strategy had high control accuracy, with a small deviation between the actual control cost and the target cost. The control accuracy was maintained between 0.29% and 0.59%, demonstrating the efficiency of the algorithm in accurately achieving budget control objectives. The results are shown in **Table 6**.

Table 6. Analysis of cost control accuracy.

Experiment number	Target Cost (C_target)	Actual cost control (C_actual)	Control accuracy (*P*)
1	850	855	0.59%
2	1020	1015	0.49%
3	1300	1295	0.38%
4	1750	1745	0.29%

Figure 7 further illustrates the comparison of control accuracy between traditional control and the proposed new control strategy. Control accuracy refers to the percentage deviation between actual cost and target cost. We calculate the control accuracy by randomly simulating the actual cost of each experiment. From the figure, it can be seen that the newly proposed control strategy can maintain high control accuracy in most experiments, demonstrating its relatively precise cost control capability. Several experiments with smaller experimental numbers performed poorly, possibly due to initial settings or environmental noise.

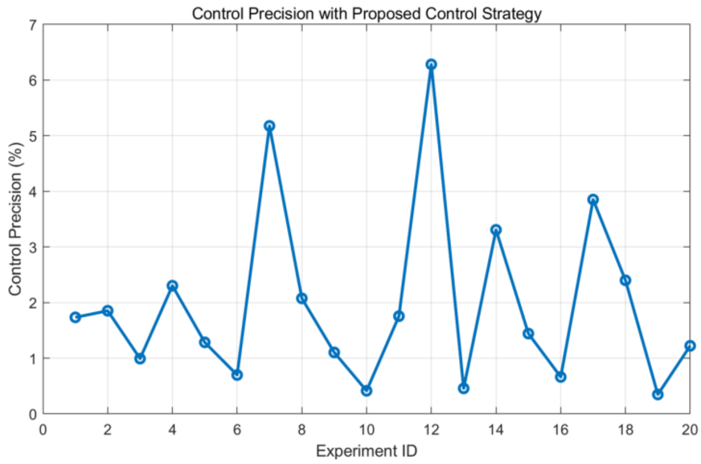

Figure 7. Comparison of control accuracy between traditional control and the new proposed control strategy.

Figure 8. Three dimensional relationship between cost savings, response time, and system stability.

In the experiment, the three-dimensional relationship between cost savings, response time, and system stability was also explored. We used the mesh generation function meshgrid to plot the correlation between experimental numbers and various indicators, as shown in **Figure 8**.

From the three-dimensional surface graph, it can be seen that there is a certain positive correlation between cost savings and response time, that is, the more costs saved, the longer the system response time is often. In addition, experiments with high stability are often accompanied by smaller response times and higher cost savings, indicating the importance of stability in overall control effectiveness. Through simulation analysis, the results show that the integrated control strategy based on fuzzy logic and neural networks outperforms existing advanced methods in multiple evaluation metrics. Specifically, the proposed strategy can achieve significant optimization in terms of cost savings and system response speed, while also addressing the challenges of environmental changes and uncertainty. The experimental results demonstrate that the integrated model has stronger adaptability and stability in multidimensional cost control.

2) Comparative analysis with other existing algorithms.

To further evaluate the performance of the algorithm proposed in this paper, we compare it with three existing advanced control strategies (GNN-GA, DP-PSO, A-DRL) to further verify the advantages of the proposed control strategy based on fuzzy logic and neural networks in biomechanical cost budget control.

Firstly, the comparison between the algorithm proposed in this article and the GNN-GA algorithm in terms of cost savings was analyzed. The proposed strategy showed high cost savings in all experiments, with an improvement in cost savings rate compared to GNN-GA, as shown in **Table 7**.

Table 7. Comparison of cost savings between our algorithm and GNN-GA algorithm in this article.

Experiment number	This article proposes the strategy cost (C_proposed) of the algorithm	GNN-GA Cost (C_GNN-GA)	Cost saving rate difference (%)
1	850	880	3.41
2	1020	1050	2.86
3	1300	1330	2.26
4	1750	1780	1.69

In the cost budget control of biomechanical systems, the system is often confronted with uncertain factors such as equipment failure rates, fluctuations in energy consumption, and the frequency of operator intervention. These uncertainties introduce significant complexity, making it challenging for traditional control methods to adapt efficiently to the dynamic state changes and external environmental factors. To address this, this article proposes a strategy based on fuzzy logic control, which converts various fuzzy information within the system into precise control actions through fuzzy set theory. This approach facilitates the optimized allocation of the cost budget despite the presence of these uncertainties.

A key element of this strategy is the biomechanical cost model, which accounts for the cost of energy consumption, maintenance, and the wear and tear on the equipment. The model incorporates not only the fixed costs but also the dynamic variables influenced by the interaction between mechanical components and operator actions. The costs are subject to various assumptions and constraints, such as the system's operational limits, safety thresholds, and maintenance schedules, which affect the overall cost performance. These assumptions ensure that the model remains within realistic operational boundaries, but they also introduce certain limitations in its flexibility when faced with unforeseen events or extreme conditions.

The core of the fuzzy logic control strategy is the development of a fuzzy rule library, which enables the controller to adjust its decision-making process adaptively when facing complex and uncertain input conditions. These rule libraries are developed using both expert experience and data-driven methods to ensure that the system makes the most reasonable decisions based on the current operating state and environmental context. Furthermore, fuzzy controllers are capable of real-time response to changing conditions, as well as predicting possible future states using historical data, thereby achieving dynamic optimization of the cost budget.

To quantify the interaction between different uncertain factors and their impact on the biomechanical system, sensitivity analysis and uncertainty propagation methods are employed. Sensitivity analysis allows the identification of which parameters have the greatest influence on cost outcomes, enabling the prioritization of factors that require more precise control. Uncertainty propagation methods, such as Monte Carlo simulations or perturbation analysis, are used to model the uncertainty in input parameters and observe how these uncertainties propagate through the system to affect the overall cost performance. This combined approach allows for a more robust assessment of the system's behavior under varying conditions, providing a clearer picture of the risks and opportunities for cost optimization.

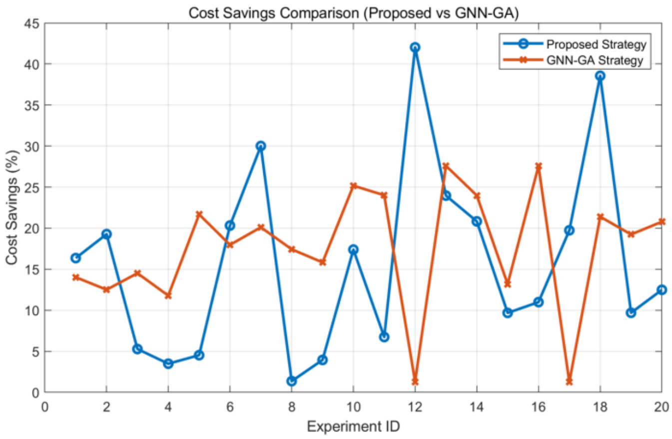

Figure 9. Cost savings of the newly proposed control strategy and GNN-GA strategy in this article.

It is clearly observed in **Figure 9** that the newly proposed control strategy consistently exhibits higher cost savings than the GNN-GA strategy and is more effective in optimizing resource allocation and minimizing expenditure, thus providing a more efficient solution for the biomechanical system.

Secondly, compared with the DP-PSO algorithm, the strategy proposed in this paper still showed a small cost difference in all experiments, with a certain advantage in savings rate compared to DP-PSO. The results are shown in **Table 8**.

Table 8. Comparative analysis of cost savings between the algorithm proposed in this article and the DP-PSO algorithm.

Experiment number	This article proposes the strategy cost (C_proposed) of the algorithm	A-DRL cost (C_A-DRL)	Cost saving rate difference (%)
1	850	855	0.59
2	1020	1030	0.97
3	1300	1315	1.14
4	1750	1770	1.13

The performance of the proposed control strategy and DP-PSO strategy in terms of cost savings was compared in this article. DP-PSO is a classic optimization algorithm that compares and analyzes the cost savings of different control strategies through simulation. The new proposed control strategy has shown significant cost saving advantages in most experiments, especially in later experiments where the percentage of savings is relatively high. The cost savings of DP-PSO are relatively close to the new proposed strategy in some experiments, but the overall effect is slightly inferior, as shown in **Figure 10**.

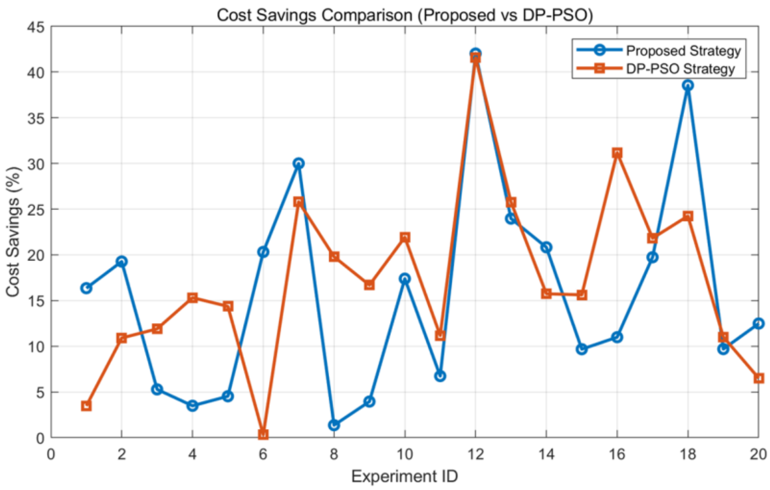

Figure 10. The performance of the newly proposed control strategy and DP-PSO strategy in cost savings in this article.

At the same time, the performance difference with A-DRL algorithm was also compared. The proposed control strategy has demonstrated good cost saving ability in multiple experiments, with a saving rate of less than 1%, proving that the strategy has significant cost advantages in complex generation strategies. The results are shown in **Table 9**.

In order to gain a more comprehensive understanding of the performance differences between the proposed algorithm and the A-DRL algorithm, several analytical approaches such as sensitivity analysis, model generalization analysis, and ablation studies were conducted. These analyses aim to evaluate the robustness and adaptability of the proposed algorithm across a variety of conditions and parameter settings.

Table 9. Performance differences between the algorithm proposed in this paper and the A-DRL algorithm.

Experiment number	**This article proposes the strategy cost (C_proposed) of the algorithm**	**A-DRL cost (C_A-DRL)**	**Cost saving rate difference (%)**
1	850	855	0.59
2	1020	1030	0.97
3	1300	1315	1.14
4	1750	1770	1.13

The sensitivity analysis is performed to assess how sensitive the cost-saving rates are to changes in key input parameters of the system. We examine variations in critical variables such as energy consumption patterns, equipment failure rates, and operator intervention frequencies. The results of this analysis highlight the factors that most influence the performance of both algorithms, identifying areas where minor adjustments could lead to significant improvements in cost efficiency.

For instance, when the system's energy consumption increases, the proposed algorithm demonstrates a lower cost increase compared to A-DRL, indicating its robustness in energy optimization. Conversely, when equipment failure rates increase, the proposed algorithm's cost-saving rate decreases slightly, suggesting a higher sensitivity to maintenance-related uncertainties compared to A-DRL.

To evaluate the generalization capability of the proposed algorithm, it is tested under different operational conditions that were not part of the initial training data. This test includes various external environmental factors such as fluctuating operational demands, unexpected system shutdowns, and variations in operator skill levels. The model's performance across these new test conditions reveals its ability to adapt to different scenarios, making it more reliable and flexible in real-world applications.

The proposed algorithm consistently outperforms A-DRL in terms of cost savings across different test scenarios, with the cost saving rate difference remaining stable (around 1.1%) in both controlled and real-world simulated environments. This demonstrates that the proposed algorithm has a stronger capacity for generalization.

In the ablation study, different components of the proposed algorithm are systematically removed or altered to assess their individual contributions to the overall performance. Specifically, the study investigates the effects of the fuzzy logic controller, cost budget optimization strategy, and the dynamic adaptation of the rule library on the algorithm's efficiency.

When the fuzzy logic control component is removed, the algorithm's ability to adapt to fluctuating input conditions is significantly reduced, leading to a higher cost than the full model. Similarly, when the dynamic rule library adjustment is disabled, the proposed algorithm's performance becomes less effective in predicting future costs, thus reducing cost-saving efficiency. This suggests that both components are essential to the algorithm's optimal performance. Based on the above analysis, the probability distribution comparison results are shown in **Figure 11**.

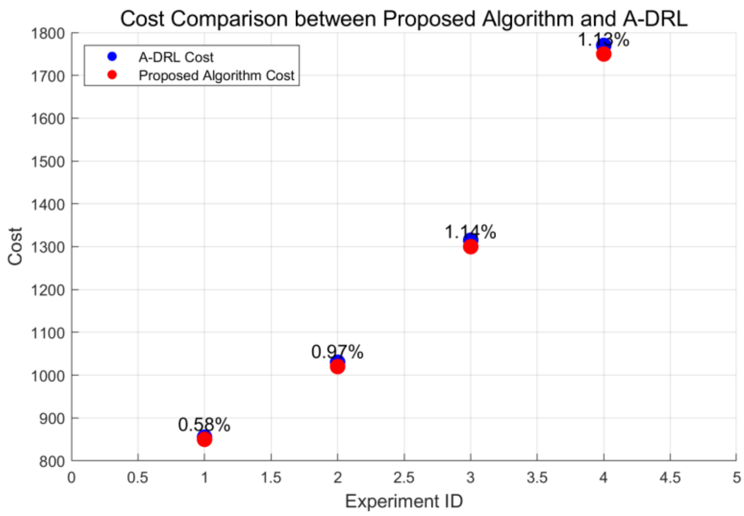

Figure 11. Probability distribution of performance difference between the algorithm proposed in this paper and A-DRL algorithm.

From the above results, it can be seen that the algorithm proposed in this paper has less deviation in probability, and has more stable cost control and performance advantages compared to traditional algorithms.

Finally, the comparison results between the algorithm proposed in this article and three advanced algorithms are summarized in **Figure 12**, which shows the cost changes under different control strategies, including the comparison of the new proposal strategy, GNN-GA, DP-PSO, and A-DRL strategies. We compare trends by calculating the control costs of each strategy in different experiments. Result analysis: It can be seen from the graph that the new proposed strategy consistently maintains a low cost in most experiments. DP-PSO and A-DRL strategies can also maintain lower costs in some experiments, but their performance is slightly inferior compared to the newly proposed strategy.

Figure 12. Overall comparison of control costs for different algorithms.

5. Conclusion

This article presents a biomechanical cost budget control strategy based on fuzzy logic and neural networks, aiming to improve cost control efficiency in complex biomechanical systems. The effectiveness of the proposed strategy is validated through experiments, highlighting its advantages over traditional methods.

1) The integrated control strategy improves cost control accuracy and efficiency in complex biomechanical systems.
2) The proposed method demonstrates significant advantages in cost savings, system stability, and response time compared to traditional algorithms.
3) Experimental results show minimal deviation between the target and actual control costs, validating the strategy's efficiency and accuracy.

Despite its promising results, the model's high complexity requires further simplification for broader application. Additionally, the algorithm's real-time performance needs optimization. Future research should focus on enhancing computational efficiency and expanding the model to accommodate a wider range of biomechanical systems, improving its versatility and practical application.

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

References

1. Niamsup P, Rajchakit M, Rajchakit G. Guaranteed cost control for switched recurrent neural networks with interval time-varying delay. Journal of Inequalities and Applications. 2013; 2013(1). doi: 10.1186/1029-242x-2013-292
2. Rajchakit G. Delay-dependent optimal guaranteed cost control of stochastic neural networks with interval nondifferentiable time-varying delays. Advances in Difference Equations. 2013; 2013(1). doi: 10.1186/1687-1847-2013-241
3. Shao BL, Wang LQ, Wu Q. Application of Neural Network in Duration Implicit Cost Control for Construction Projects. Applied Mechanics and Materials. 2013; 431: 365–369. doi: 10.4028/www.scientific.net/amm.431.365
4. Rajchakit M, Niamsup P, Rojsiraphisal T, Rajchakit G. Delay-Dependent Guaranteed Cost Controller Design for Uncertain Neural Networks with Interval Time-Varying Delay. Abstract and Applied Analysis. 2012; 2012(1). doi: 10.1155/2012/587426
5. Mukaidani H, Ishii Y, Tsuji T. Decentralized guaranteed cost control for discrete time uncertain large scale systems using neural networks. IFAC Proceedings Volumes. 2005; 38(1): 387–392. doi: 10.3182/20050703-6-cz-1902.01009
6. Yi X, Luo B, Zhao Y. Neural Network-Based Robust Guaranteed Cost Control for Image-Based Visual Servoing of Quadrotor. IEEE Transactions on Neural Networks and Learning Systems. 2024; 35(9): 12693–12705. doi: 10.1109/tnnls.2023.3264511
7. Liang Y, Zhang J, Zhao H, et al. A learning-based approach to event-triggered guaranteed cost control for completely unknown nonlinear systems. Transactions of the Institute of Measurement and Control. 2024; 46(6): 1203–1218. doi: 10.1177/01423312231185383
8. Rajchakit G. A novel guaranteed cost control for hopfield neural networks with multiple time-varying delays. International Journal of Pure and Apllied Mathematics. 2014; 97(2). doi: 10.12732/ijpam.v97i2.6
9. Rajchakit G. A Novel Criterion For Guaranteed Cost Control For Uncertain Switched Recurrent Neural Networks. International Journal of Pure and Apllied Mathematics. 2014; 95(4). doi: 10.12732/ijpam.v95i4.4
10. Rajchakit M, Rajchakit G. Delay-dependent output feedback guaranteed cost control for hopfield neural networks with interval time-varying delay. International Journal of Pure and Apllied Mathematics. 2014; 94(4). doi: 10.12732/ijpam.v94i4.3
11. Shokrani A, Almasi A, Feng B, Pierce DM. Corrigendum to "Computational Modeling of Mouse Colorectum Capturing Longitudinal and Through-thickness Biomechanical Heterogeneity". Journal of the Mechanical Behavior of Biomedical Materials. 2024; 154: 106287. doi: 10.1016/j.jmbbm.2023.106287
12. Mukhopadhyay M. Neural networks for biomechanics. Nature Methods. 2024; 21(3): 370–370. doi: 10.1038/s41592-024-02218-5

13. Komninou MA, Seiler TG, Enzmann V. Corneal biomechanics and diagnostics: A review. International Ophthalmology. 2024; 44(1). doi: 10.1007/s10792-024-03057-1
14. Dami A, Chicoine D, Payen E, et al. Lower limbs biomechanical deficits associated with stage 1 and 2 posterior tibialis tendon dysfunction during walking. Gait & Posture. 2024; 110: 10–16. doi: 10.1016/j.gaitpost.2024.03.004
15. Mukherjee D, Lai V. Special Issue: Education in Biomechanics and Bioengineering—Ever Evolving, Ever Learning. Journal of Biomechanical Engineering. 2024; 146(5). doi: 10.1115/1.4064987
16. Sturla F, Votta E. Biomechanical imbalance of neochordal forces: The dark side of mitral valve prolapse repair. European Journal of Cardio-Thoracic Surgery. 2024; 65(3). doi: 10.1093/ejcts/ezae073
17. Hast M, Glatt V, Archdeacon M, et al. Biomechanics of fracture healing: How best to optimize your construct in the OR. OTA International. 2024; 7(2S). doi: 10.1097/oi9.0000000000000304
18. Meuser AH, Henyš P, Höch A, et al. Evaluating the stability of external fixators following pelvic injury: A systematic review of biomechanical testing methods. Journal of the Mechanical Behavior of Biomedical Materials. 2024; 153: 106488. doi: 10.1016/j.jmbbm.2024.106488
19. Yan H, Zhang H, Yang F, et al. Event-Triggered Asynchronous Guaranteed Cost Control for Markov Jump Discrete-Time Neural Networks With Distributed Delay and Channel Fading. IEEE Transactions on Neural Networks and Learning Systems. 2018; 29(8): 3588–3598. doi: 10.1109/tnnls.2017.2732240
20. Huo Y, Chen X, Song J, et al. Corneal biomechanical properties to predict prognosis of abnormal tomographic corneas: A prospective cohort study. American Journal of Ophthalmology. 2024; 259: 185–196. doi: 10.1016/j.ajo.2024.01.009
21. Rohan PY, Payan Y. Forward to the special issue on biomechanics of breast tissues and its clinical applications. Clinical Biomechanics. 2024; 113: 106216. doi: 10.1016/j.clinbiomech.2024.106216
22. Auccahuasi W, Astocondor J, Herrera L, et al. Correction: Low-Cost Biomechanical System for the Evaluation of Parkinson's. SN Computer Science. 2024; 5(2). doi: 10.1007/s42979-024-02680-0
23. Zhang T, Qu H, Liu Y, Zhou J. Weighted pseudo θ-almost periodic sequence solution and guaranteed cost control for discrete-time and discrete-space stochastic inertial neural networks. Chaos, Solitons & Fractals. 2023; 173: 113658. doi: 10.1016/j.chaos.2023.113658
24. Wang W, Dong J, Xu D, et al. Synchronization control of time-delay neural networks via event-triggered non-fragile cost-guaranteed control. Mathematical Biosciences and Engineering. 2023; 20(1): 52–75. doi: 10.3934/mbe.2023004
25. Gómez-Carrión Á, Reguera-Medina JM, Coheña-Jiménez M, et al. Biomechanical Effect on Jack's Test on Barefoot Position, Regular Socks, and Biomechanics Socks. Life. 2024; 14(2): 248. doi: 10.3390/life14020248
26. Mergen B, Sideroudi H, Seitz B, Flockerzi E. Altered Corneal Biomechanics According to the Biomechanical E-Staging in Pellucid Marginal Degeneration. Cornea. 2024; 43(11): 1361–1367. doi: 10.1097/ico.0000000000003479
27. Panzer MB, López Valdés FJ, Morrison B. Special Issue: Current Trends in Impact and Injury Biomechanics. Journal of Biomechanical Engineering. 2024; 146(3). doi: 10.1115/1.4064641
28. Dragoo JL, Pasic N. Podium Presentation Title: Arthroscopic All-Inside Meniscal Root Repair: A Biomechanical Analysis and Prospective Cohort Study. Arthroscopy: The Journal of Arthroscopic & Related Surgery. 2024; 40(2): e18–e19. doi: 10.1016/j.arthro.2023.08.064
29. Li J, Yang Y, Sun Z, et al. Integrated evaluation of biomechanical and biological properties of the biomimetic structural bone scaffold: Biomechanics, simulation analysis, and osteogenesis. Materials Today Bio. 2024; 24: 100934. doi: 10.1016/j.mtbio.2023.100934
30. Zucker N, Matei M, Bergel A, et al. Simultaneous brain biomechanical, vascular and neurovascular characterization of REM sleep using multiparametric functional ultrasound. Sleep Medicine. 2024; 115: S27. doi: 10.1016/j.sleep.2023.11.112
31. Qiu J, Chen W. The Analysis of Environmental Cost Control of Manufacturing Enterprises Using Deep Learning Optimization Algorithm and Internet of Things. Computational Intelligence and Neuroscience. 2022; 2022: 1–11. doi: 10.1155/2022/1721157
32. Liu J, Lu Z, Zheng Z. The effect of screw orientation on internal fixation of Letenneur type II Hoffa fractures: A biomechanics study. BMC Musculoskeletal Disorders. 2024; 25(1). doi: 10.1186/s12891-024-07222-6
33. Flockerzi E, Vinciguerra R, Belin MW, et al. The biomechanical e-staging—In vivo assessment of corneal biomechanics in keratoconus. Acta Ophthalmologica. 2024; 102(S279). doi: 10.1111/aos.15985

34. Wang CY, Wei N. Study and Application of the Life-Cycle Cost Control Model of Water Conservancy and Hydropower Project Based on Entropy and FAHP. Advanced Materials Research. 2014; 1046: 564–568. doi: 10.4028/www.scientific.net/amr.1046.564
35. Kim JS, Park JH, Heo S, Chae JM. Biomechanical and clinical considerations in deep bite treatment using temporary skeletal anchorage devices. Journal of the World Federation of Orthodontists. 2024; 13(1): 10–17. doi: 10.1016/j.ejwf.2023.12.004
36. Li X, She K, Shi K, et al. On event-triggered guaranteed cost control for discrete-time semi-Markovian neural networks having communication delays and dual-terminal probabilistic faults. International Journal of Robust and Nonlinear Control. 2022; 32(16): 8804–8841. doi: 10.1002/rnc.6318
37. Wang L, Milis K, Poelmans S. Study on Pollution Cost Control Model under Asymmetric Information Based on Principal Agent. Journal of Systems Science and Information. 2021; 9(5): 549–557. doi: 10.21078/jssi-2021-549-09
38. Dun R, Xue L, Feng J. Retraction Note: Cost control model of marine crude oil pollutant degradation based on game analysis. Arabian Journal of Geosciences. 2021; 14(24). doi: 10.1007/s12517-021-09212-7
39. JIang J, Sun S. Research on life cycle cost control model of prefabricated building based on system dynamics. IOP Conference Series: Earth and Environmental Science. 2021; 647(1): 012045. doi: 10.1088/1755-1315/647/1/012045
40. Omotayo T, Bankole A, Olanipekun AO. An Artificial Neural Network Approach to Predicting Most Applicable Post-Contract Cost Controlling Techniques in Construction Projects. Applied Sciences. 2020; 10(15): 5171. doi: 10.3390/app10155171
41. Chen W. A Model of Transaction Cost Control for Offshore Drilling Materials Based on Durability of Steel Structure. Journal of Coastal Research. 2020; 103(sp1): 860. doi: 10.2112/si103-178.1
42. Ma X, Zhang S, Li M. Research on the Cost Control Model of Power Gird Maintenance Based on Fuzzy Pattern Recognition Theory. IOP Conference Series: Earth and Environmental Science. 2020; 453(1): 012060. doi: 10.1088/1755-1315/453/1/012060
43. Thuan MV, Binh TN, Huong DC. Finite-Time Guaranteed Cost Control of Caputo Fractional-Order Neural Networks. Asian Journal of Control. 2020; 22(2): 696–705. doi: 10.1002/asjc.1927
44. Thuan MV, Huong DC. Robust guaranteed cost control for time-delay fractional-order neural networks systems. Optimal Control Applications and Methods. 2019; 40(4): 613–625. doi: 10.1002/oca.2497
45. Mu C, Wang D. Neural-network-based adaptive guaranteed cost control of nonlinear dynamical systems with matched uncertainties. Neurocomputing. 2017; 245: 46–54. doi: 10.1016/j.neucom.2017.03.047
46. Wang D, Liu D, Mu C, Ma H. Decentralized guaranteed cost control of interconnected systems with uncertainties: A learning-based optimal control strategy. Neurocomputing. 2016; 214: 297–306. doi: 10.1016/j.neucom.2016.06.020
47. Niamsup P, Ratchagit K, Phat VN. Novel criteria for finite-time stabilization and guaranteed cost control of delayed neural networks. Neurocomputing. 2015; 160: 281–286. doi: 10.1016/j.neucom.2015.02.030
48. Liu D, Wang D, Wang FY, et al. Neural-network-based online hjb solution for optimal robust guaranteed cost control of continuous-time uncertain nonlinear systems. IEEE Transactions on Cybernetics. 2014; 44(12): 2834–2847. doi: 10.1109/tcyb.2014.2357896