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Artificial Intelligence in Mathematical Modelling of Complex Systems

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Abstract

This article introduces artificial intelligence techniques in mathematical modelling of complex systems and their applications. Mathematical modelling of complex systems is a method of studying the structure and behaviour of complex systems, aiming to understand interactions and nonlinear effects in the system. Commonly used modelling methods include system dynamics, network theory, and algebraic methods. Artificial intelligence technologies include machine learning and deep learning, which can be used for tasks such as prediction and classification, anomaly detection, optimization and decision-making. In mathematical modelling of complex systems, artificial intelligence technology can learn system patterns and laws from large amounts of data, and can be applied to image and speech recognition, time series analysis and other fields. Deep learning and machine learning are important branches of artificial intelligence. They realize the modelling and analysis of complex systems by building neural network models. Data-driven modelling is a modelling method based on actual data that, combined with traditional theoretical modelling, can better describe and predict the behaviour of complex systems. Self-control of complex systems means that the system realizes its own optimization and adjustment through adaptive control algorithms and feedback mechanisms. In summary, artificial intelligence technology has broad application prospects in mathematical modelling of complex systems and will provide new tools and methods for in-depth understanding and solving problems in complex systems.

Keywords: Mathematical Modelling of Complex Systems, Artificial Intelligence Technology, Machine Learning and Deep Learning, Data-driven modelling, Adaptive Control of Complex Systems

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1. Mathematical Modelling of Complex Systems

Mathematical modelling of complex systems involves the use of mathematical equations and techniques to understand, analyze, and predict the behavior of systems composed of [illegible] interconnected components [1]. These systems can be found in various fields such as physics, biology, ecology, economics and sociology. As shown in the Figure 1 below, the following process can generally be followed when it comes to mathematical modeling of complex systems.

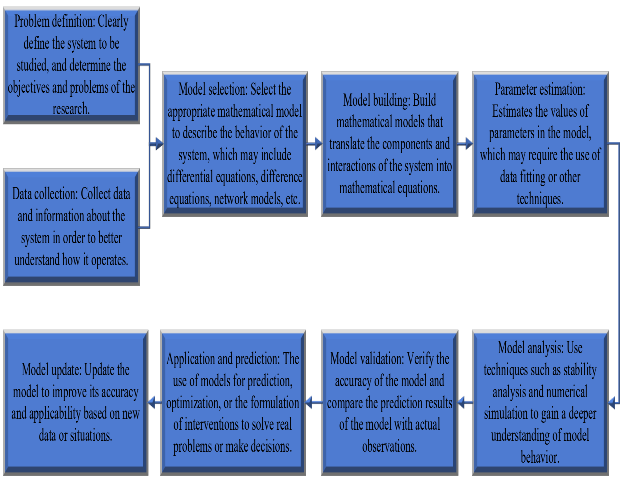

Figure 1. The mathematical modeling process of complex systems

The choice of mathematical model depends on the specific characteristics of the system under study [2]. Different models can include differential equations, difference equations, network models, met acellular automata, agent-based models [3], or stochastic models, etc. Choosing an appropriate model is critical as it should capture the essential characteristics of the system while being computationally tractable.

After a mathematical model is built, its behavior can be analyzed using a variety of analytical and computational techniques [4]. These techniques may include stability analyses, bifurcation analyses, numerical simulations, optimization methods, or sensitivity analyses. The goal is to gain insights into the behavior of the system, identify key parameters, and predict its response to different conditions or interventions.

Mathematical modeling of complex systems has many applications [5]. For example, it can be used to understand the spread of infectious diseases, predict the behavior of financial markets, optimize transportation networks, study the dynamics of ecosystems, or simulate social interactions. These models can provide valuable insights to help inform informed decisions and guide the design of interventions or policies [6].

In summary, mathematical modeling of complex systems is a powerful tool for understanding, analyzing, and predicting the behavior of systems with many interacting components. It plays a vital role in various disciplines and can provide valuable insights for decision making and problem-solving. However, careful formulation, analysis and validation of the model is crucial to ensure its accuracy and reliability. Paper structure in Figure 2:

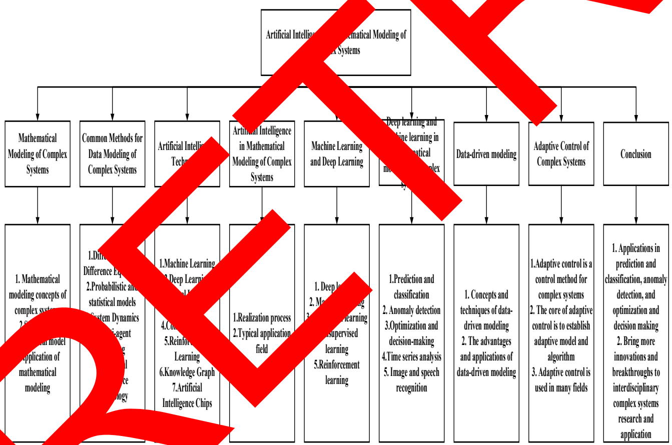

Figure 2. Paper structure

2. Common Methods for Data Modelling of Complex Systems

Mathematical modeling of complex systems involves the use of mathematical methods and techniques to describe and analyze systems that are composed of multiple interrelated components and often have nonlinear and dynamic properties [7]. As shown in the Table 1, the following are some methods often used in mathematical modeling of complex systems:

Table 1. Different mathematical modeling methods and their application fields

Methods	Description	Application Fields
Differential Equations and Difference Equations	Used to describe the dynamic behavior of a system, involving interactions and changes between components	Biology, chemistry, physics, economics
Algebraic Equation	Used to describe a static relationship in a system, that is, the state of the system at a point in time	Economics, engineering, social sciences
Probabilistic and Statistical Models	Used to describe randomness and uncertainty in systems, including Markov chains, Monte Carlo simulation	Finance, meteorology, medicine
Graph Theory and Network Model	Used to represent the relationships between various components in a system, helping to understand system structure and information dissemination	Social network analysis, Internet research, power system optimization
System Dynamics	Used to quantitatively	Environmental studies,

	analyze causality in complex systems and describe the interaction between system variables	management, political science
Chaos Theory	Used to describe and analyze chaotic phenomena in complex systems and capture the complex and unpredictable nature of systems	Weather prediction, stock market fluctuations, heart physiology
Multi-agent Modeling	Agent-based methods are used to simulate the behavior and interaction of multiple independent individuals and analyze the overall behavior of the system	Traffic flow simulation, market competition analysis, natural resource management
optimization method	Used to determine system parameters or structures to achieve optimization of specific goals, including evolutionary algorithms, genetic algorithms	Engineering optimization, production planning, supply chain management
AIT (artificial intelligence technology)	This includes machine learning and deep learning for generating models, predicting system behavior, optimizing performance, and more	Data mining, intelligent transportation, medical diagnosis
Theory of Control	Used to design system controllers and adjust system state to achieve stability and performance goals	Robot control, aircraft navigation, automated production line

Differential and Difference Equations: Differential and difference equations are common tools for describing the dynamic behavior of systems [8]. They are used to represent interactions and changes between components in a system. Algebraic equations [9]: Algebraic equations are often used to describe static relationships in a system, that is, the state of the system at a certain point in time. This is useful for analyzing the balance and stability of a system.

Probabilistic and statistical models: Complex systems often contain randomness and uncertainty. Probabilistic and statistical models, such as Markov chains, Monte Carlo simulations, etc., are used to describe random changes and uncertainties in systems [10]. Graph theory and network models: Graph theory and network models are used to represent the relationships between components in a system. Complex network analysis can help understand the structure of a system, how nodes are connected, and the paths through which information travels.

System Dynamics: System dynamics is a method of quantitatively analyzing cause-and-effect relationships in complex systems [11]. It uses tools such as Coulomb diagrams and flow charts to describe the interactions between variables in the system. Chaos theory: For complex systems that exhibit chaotic phenomena, chaos theory provides a method to describe and analyze system behavior [12]. Nonlinear dynamics and chaos models can be used to capture the complex and unpredictable nature of systems.

Multi-agent modeling: For systems containing multiple individuals or agents, the multi-agent modeling method (Agent-Based Modeling) is widely used [13]. Each individual is treated as an independent agent whose actions and decisions are based on its surrounding environment and interactions with other agents. Optimization methods: Optimization methods can be used to determine system parameters or adjust the system structure to achieve specific goals. Methods such as evolutionary algorithms, genetic algorithms, and particle swarm algorithms are often used to solve optimization problems in complex systems

[14].

Artificial Intelligence Technology [15]: Artificial Intelligence technology, especially machine learning and deep learning, is widely used in generating models from complex systems, predicting system behavior, optimizing system performance, etc. Control Theory: Control theory is used to design controllers that can regulate the state of a system to achieve its stability and performance goals [16].

Mathematical modeling of complex systems is an interdisciplinary field that requires combining knowledge from multiple fields such as mathematics, physics, and computer science. By employing a variety of mathematical modeling methods, researchers are able to better understand and predict the behavior of complex systems, allowing them to make more informed decisions and optimize system performance.

3. Artificial Intelligence Technology

Artificial Intelligence (AI) [17, 18] technology is a research field dedicated to enabling computer systems to perform intelligent behaviors similar to humans [19]. Artificial intelligence technology includes a variety of methods and algorithms designed to enable computer systems to perceive, understand, learn, reason, and perform tasks [15]. From to Figure 3, here are some common artificial intelligence technologies:

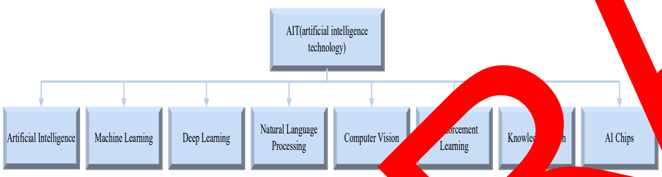

Figure 3. Artificial intelligence related technologies

Machine Learning: Machine learning is an artificial intelligence method that aims to enable computer systems to perform tasks by learning patterns and regularities from data without having to be explicitly programmed [20]. Machine learning includes a variety of algorithms, such as decision trees, support vector machines, K nearest neighbors, etc. These algorithms can be classified through supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning [21].

Deep Learning: Deep learning [22, 23] is a branch of machine learning that focuses on using deep neural networks, [illegible] containing multiple layers of neural networks, to model and solve complex problems [24]. The characteristic of deep learning is that it can automatically learn high-level abstract features and represent data through these features. Deep learning excels at handling large-scale data and complex tasks.

Natural Language Processing (NLP): It is an important branch in the field of artificial intelligence and studies the interaction and communication between computers and human natural language [25]. It involves the understanding, generation, processing and analysis of text and speech, aiming to enable computers to understand and process human language. Natural language processing is widely used in many fields, such as intelligent assistants, machine translation, public opinion analysis, text mining, automatic question and answer system [26].

Computer Vision: Computer Vision (Computer Vision) is an important branch in the field of artificial intelligence [27]. It studies how to enable computers to simulate and understand the human visual system and realize the understanding, analysis and processing of images and videos [28, 29]. The goal of computer vision is to enable computers to extract useful information from image and video data, including image classification, target detection, image segmentation, pose estimation, action recognition [30].

Reinforcement Learning: Reinforcement learning is a method of learning decision-making strategies by taking actions in the environment. The agent receives feedback (reward or punishment) from the environment to optimize its behavior [31]. This is widely used in the field of autonomous decision making and control. The combination of reinforcement learning, and deep learning can build a deep reinforcement learning model and use deep learning for value function estimation and policy optimization in reinforcement learning.

Knowledge Graph: A knowledge graph is a graphical structure used to represent and organize knowledge. It can help computer systems understand the relationships between entities and facilitate reasoning and problem solving [32]. Recommendation System: Recommendation system uses machine learning algorithms to analyze user behavior and preferences to predict and recommend content, products or services that may be of interest to the user.

Artificial Intelligence Chips (AI Chips): In order to meet the needs of artificial intelligence model training and inference, specially designed hardware accelerators, such as graphics processing units (GPUs), tensor processing units (TPUs), etc., are widely used to improve computing efficiency [33]. Autonomous Driving technology uses computer vision, sensor fusion, reinforcement learning and other technologies to enable vehicles to perform navigation and driving tasks without human intervention [34]. Swarm Intelligence imitates collaboration and collective behavior in social groups and is used in fields such as optimization problems and routing planning.

These artificial intelligence technologies have made remarkable progress in various fields and have had a profound impact on society, science, and industry. Its continuous innovation and application are expected to further promote the development of the field of artificial intelligence.

4. Artificial Intelligence in Mathematical Modelling of Complex Systems

Artificial intelligence has extensive applications in mathematical modeling of complex systems [35]. Through technologies such as machine learning and deep learning, artificial intelligence can learn from large amounts of data and discover patterns and regularities in the system. This ability allows artificial intelligence to better understand and solve problems in complex systems. Like that Figure 4 here, implementation flow of artificial intelligence in mathematical modeling of complex systems.

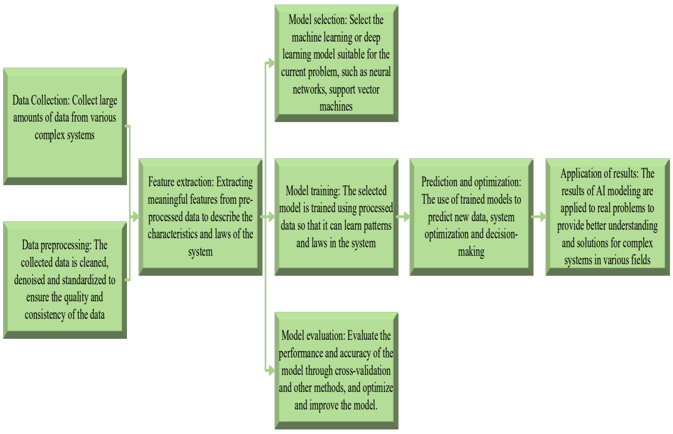

Figure 4. Implementation flow of artificial intelligence in mathematical modeling of complex systems

In the modeling of biological systems, artificial intelligence can reveal complex relationships and mechanisms in biological systems by analyzing biological data and simulating biological processes [36]. For example, by analyzing genomic data, AI can predict associations between genes and diseases, as well as interactions between genes. From to Figure 5, this is of great significance for disease prevention, drug development and other aspects.

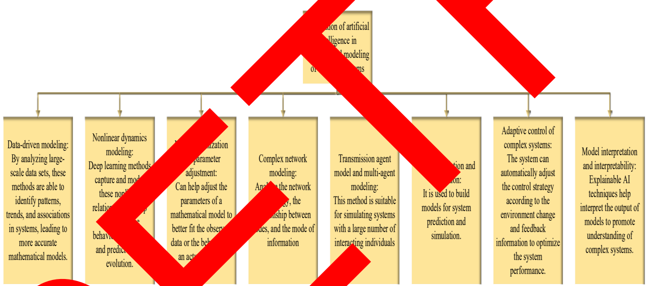

Figure 5. Application of artificial intelligence in mathematical modeling of complex systems

In the modeling of social systems, artificial intelligence can reveal the complexity and dynamics in social systems by analyzing social network data and human behavior patterns [37]. For example, by analyzing social network data, artificial intelligence can predict people's interests and behaviors and help companies conduct precise marketing; by analyzing traffic data, artificial intelligence can optimize traffic flow and improve urban transportation efficiency.

In addition, artificial intelligence can also be applied to complex system modeling in various fields such as financial systems, energy systems, and environmental systems [38]. By analyzing large amounts of historical and real-time data, artificial intelligence can predict market trends, optimize energy utilization [39], improve environmental protection effects, etc. The following are some typical application areas:

Data-driven modeling: Artificial intelligence techniques, especially machine learning and deep learning, are widely used in data-driven modeling of complex systems [40]. By analyzing large-scale data sets, these methods are able to identify patterns, trends, and correlations in systems to build more accurate mathematical models.

Nonlinear dynamics modeling: Complex systems usually exhibit nonlinear dynamics [41]. Deep learning methods can be used to capture and model these nonlinear relationships, helping to understand the behavior of the system and predict future evolution.

Model optimization and parameter adjustment: Artificial intelligence technology can be used for model optimization and parameter adjustment [42]. Optimization algorithms, such as genetic algorithms, particle swarm algorithms, and simulated annealing, can help adjust the parameters of mathematical models to better fit observed data or the behavior of actual systems.

Complex network modeling: Artificial intelligence plays a key role in modeling complex networks [43]. Machine learning methods can be used to analyze network topology, relationships between nodes, and information propagation patterns, which are very important for understanding systems with complex structures such as social networks and biological networks.

Agent Model vs. Multi-Agent Modeling: Agent models and multi-agent modeling methods in artificial intelligence are applied to describe the behavior of independent decision-making entities in the system [13]. This method is suitable for simulating systems with a large number of interacting individuals, such as economic systems or ecological systems.

Model prediction and simulation: Machine learning and deep learning can be used to build models to predict and simulate systems [44]. This is useful for evaluating system behavior under different conditions, predicting future states, and for decision support.

Adaptive control of complex systems: Artificial intelligence techniques such as reinforcement learning can be used for adaptive control of complex systems [45]. The system can automatically adjust the control strategy based on environmental changes and feedback information to optimize system performance.

Model explanation and interpretability: As the complexity of machine learning models increases, it becomes increasingly important to explain the model's decision-making process [46]. Explainable AI techniques help explain model outputs, making decisions more trustworthy and promoting understanding of complex systems.

These application examples highlight the diversity and flexibility of artificial intelligence in mathematical modeling of complex systems. By combining traditional mathematical modeling methods with modern artificial intelligence techniques, researchers are able to more fully understand and analyze the behavior of complex systems.

5. Machine Learning and Deep Learning

Deep learning is a specific branch of machine learning that simulates and imitates the structure and function of neural networks in the human brain [47]. Deep learning [48, 49] improves the model's ability to understand and represent data by building a deep neural network model. Deep learning has achieved great success in fields such as computer vision and natural language processing. The differences between deep learning and machine learning are shown in the Table 2 below.

Table 2. The difference between deep learning and machine learning

Features	Deep Learning	Machine Learning
Definition	A learning method simulating the structure and function of human brain neural network	A way for computers to learn and improve from data
Neural network structure	Construct a deep neural network model	Use different algorithms and techniques to learn from data
Data understanding and presentation skills	Improve the model's ability to understand and represent data	Learn and make predictions based on data features
Area of application	Computer vision, natural language processing and other fields	Applications in many fields, such as finance, medical care, transportation

Machine learning is a broader concept that encompasses a variety of methods and techniques designed to enable computers to learn and improve from data [50]. Machine learning methods can be divided into supervised learning, unsupervised learning and reinforcement learning.

Supervised learning is one of the most common machine learning methods. It uses labeled data as training samples, allowing the machine learning algorithm to learn the mapping relationship between input data and output labels [51]. In supervised learning, the goal of the model is to make predictions on new unlabeled data. Common supervised learning algorithms include linear regression, logistic regression, decision trees, support vector machines [52], etc.

Unsupervised learning is a machine learning method without labels that aims to discover patterns and structures from unlabeled data [53]. Unsupervised learning algorithms can perform tasks such as clustering, dimensionality reduction, and association rule mining. Common unsupervised learning algorithms include K-means clustering, principal component analysis, association rules, etc.

Reinforcement learning is a technique for learning to obtain maximum rewards from the environment. It trains agents through trial and error and feedback [54]. In reinforcement learning, an agent interacts with the environment to maximize long-term cumulative rewards by observing the state of the environment and taking actions. Reinforcement learning algorithms can be used to solve control problems, game strategies [55], etc.

In general, from to Figure 6, deep learning is a branch of machine learning that improves the model's ability to understand and represent data by building a deep neural network model.

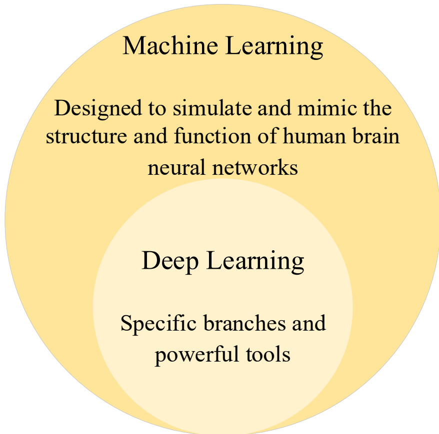

Figure 6. The connection between deep learning and machine learning

Machine learning encompasses a variety of methods and techniques, including supervised learning, unsupervised learning, and reinforcement learning, for learning and improving from data [21]. Deep learning is a powerful tool for machine learning and has achieved major breakthroughs and applications in many fields.

6. Deep learning and machine learning in mathematical modelling of complex systems

From to Figure 7, machine learning and deep learning have wide applications in mathematical modeling of complex systems [56]. Through machine learning and deep learning technology, we can learn from large amounts of data and discover patterns and laws in the system, helping to understand and solve complex problems in biological systems, social systems and other fields.

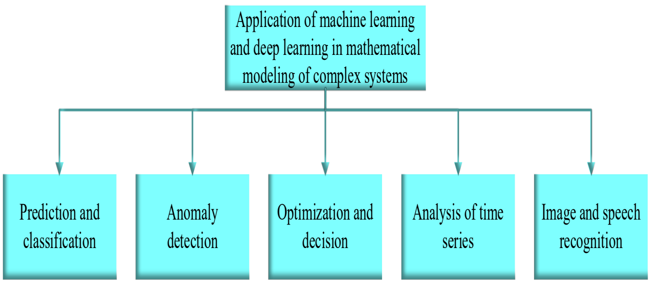

Figure 7. Application of machine learning and deep learning in mathematical modeling of complex systems

1.Prediction and classification: In complex systems, machine learning and deep learning can be used for prediction and classification [57]. By learning and discovering patterns and regularities from large amounts of data, prediction models and classification models can be built to predict future trends and classify new technologies. The data. By training deep neural networks, we learn the inherent laws and patterns of the system from the input data and then classify and predict new data [58]. For example, in biological systems, deep learning technology can be used to identify and classify different types of cells, thereby helping researchers better understand the structure and function of biological systems. By training machine learning models, future trends and behavior of complex systems can be predicted [59]. For example, in the financial field, machine learning can be used to predict the rise and fall of stock prices. In the medical field, machine learning can be used to predict disease progression and patient outcomes. In addition, machine learning can also be used for classification problems, such as identifying objects in images or determining the emotional tendency of text.

2. Anomaly detection: Secondly, machine learning and deep learning can also be applied to anomaly detection [60]. Various anomalies and mutations often exist in complex systems, and these anomalies may have an important impact on the normal operation of the system. By training a deep neural network, the normal pattern of the system can be learned, allowing it to detect anomalies and respond promptly [61]. By training machine learning models, normal behavior and abnormal behavior can be distinguished, and abnormal situations can be discovered and handled in a timely manner. This has important application value in the financial field, network security and other fields. This is very important to ensure the stable operation and security of the system. For example, in power systems, machine learning models can be used to detect abnormal loads or potential power failures [62].

3.Optimization and decision-making: In addition, machine learning and deep learning can also be applied to optimization and decision-making [63]. Help optimize the operation and decision-making process of complex systems by learning the dynamics and objective function of the system, and find optimal solutions by analyzing large amounts of data and simulating different decision-making options [64]. For example, deep learning technology can be used to optimize supply chain logistics and inventory management, reduce costs and increase efficiency. For example, in the transportation field, machine learning can be used to optimize the timing of traffic lights and reduce traffic congestion [65].

4. Time series analysis: Machine learning and deep learning can be used for the analysis and modeling of time series data [66]. By learning patterns and trends in time series data, time series models can be built to predict future trends and analyze features in time series data.

5. Image and speech recognition: Machine learning and deep learning can be used for image and speech recognition and understanding [67]. By learning a large amount of image and speech data, image recognition models and speech recognition models can be built to achieve automatic recognition and understanding of images and speech.

In general, machine learning and deep learning are widely used in mathematical modeling of complex systems, which can help understand and solve problems in complex systems and provide intelligent decision-making and optimization capabilities [68].

7. Data-driven modeling

As shown in the Figure 8, data-driven modeling is a data-based modeling method that uses a large amount of actual observation data to discover the patterns and laws of the system and transforms it into a mathematical model [69]. The core idea of this method is that the data itself contains the behavior and characteristics of the system. Through the analysis and modeling of the data, the behavior of the system can be more accurately described and predicted [70].

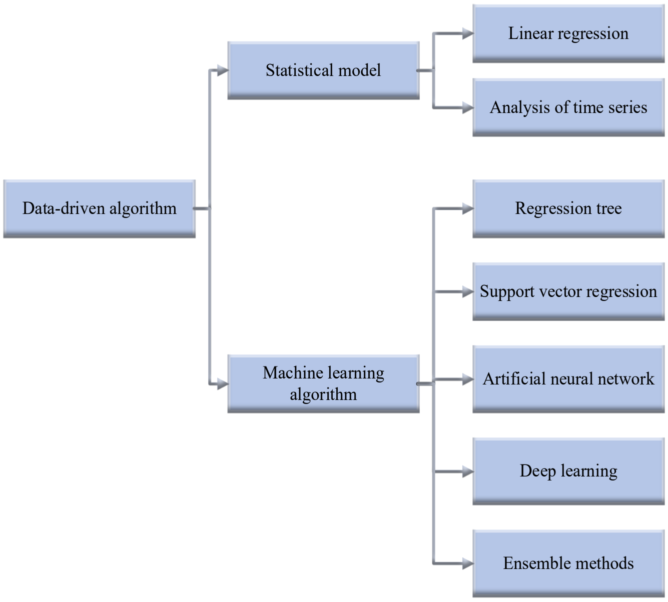

Figure 8. Data-driven algorithm

In data-driven modeling, methods such as machine learning and statistics are generally used to process and analyze data [71]. Among them, machine learning is a method of learning rules and patterns from data through training algorithms, which can automatically discover features in data and build corresponding mathematical models. Statistics is a method of inferring and modeling system behavior through statistical analysis of data [72]. Probability and statistical principles can be used to describe the distribution and correlation of data.

The advantage of data-driven modeling is its ability to extract the actual behavior of a system from the data without relying on a priori knowledge of the system or theoretical assumptions [73]. Through a large amount of data observation and analysis, data-driven modeling can more comprehensively consider the nonlinearity and complexity of the system, and can capture subtle changes and anomalies in the system [74].

Data-driven modeling has wide applications in many fields. For example, in the financial field, data-driven modeling can be used to predict stock prices, risk management and investment decisions [75], etc. In the field of biomedicine, data-driven modeling can be used to study disease development and treatment effects. In the industrial sector, data-driven modeling can be used to optimize production processes and predict equipment failures, among other things [76].

In general, data-driven modeling is a data-based modeling method that can more accurately describe and predict the behavior of the system through the analysis and modeling of a large amount of actual observation data and has wide application value.

8. Adaptive Control of Complex Systems

Adaptive control of complex systems refers to automatically adjusting control strategies and parameters according to the current status of the system and environmental changes through monitoring and analysis of the system to achieve regulation and optimization of system behavior [77]. Adaptive control has important application value in complex systems and can improve system performance and stability.

As shown in the Figure 9, a typical model reference adaptive control system is a parallel operation of the reference model and the controlled system, and the reference model represents the performance requirements of the control system. On the one hand, the input r(t) is sent to the controller to control the process, and the output of the system is y(t); On the other hand, r(t) is sent to the reference model, whose output is y m(t), reflecting the expected quality requirements. y(t) and y m(t) are compared, and the deviation is sent to the adaptive mechanism, and then the controller parameters are changed, so that y(t) can better approach y m(t).

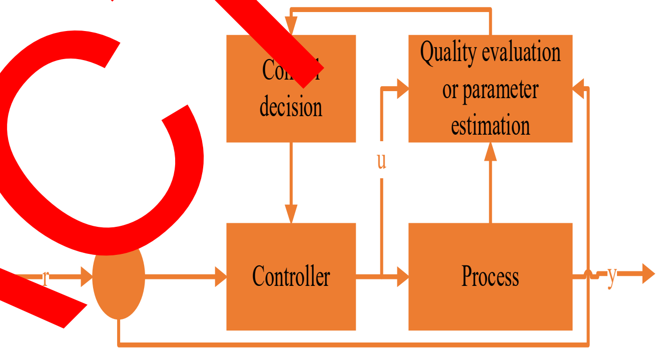

Figure 9. Structure block diagram of adaptive control system

In complex systems, due to the complexity and uncertainty of the system, traditional fixed control strategies and parameters may not be able to adapt to system changes and fluctuations [78]. Adaptive control can adjust control strategies and parameters according to the actual situation of the system to adapt to different working conditions and environmental changes by monitoring and analyzing the status and behavior of the system in real time [79].

The core of adaptive control is to establish adaptive models and algorithms [80]. Adaptive models can learn the patterns and laws of the system from large amounts of data through technologies such as machine learning and deep learning to predict the future behavior of the system and adjust control strategies [81]. The adaptive algorithm is used to automatically adjust control parameters and strategies based on the model's prediction results and actual observation data to achieve optimal and stable control of the system [82].

Adaptive control has applications in many fields, such as industrial control, traffic management, power systems, water conservancy projects [83], etc. Through adaptive control, the robustness and adaptability of the system can be improved, allowing the system to automatically adapt to different working conditions and changes, thereby improving system efficiency and performance [84].

9.Conclusion

Through technologies such as machine learning and deep learning, artificial intelligence can learn from large amounts of data and discover patterns and rules in the system, helping to understand and solve complex problems in biological systems, social systems and other fields [84]. In terms of mathematical modeling of complex systems, the applications of artificial intelligence include prediction and classification, anomaly detection, and optimization and decision-making [85].
In terms of prediction and classification, artificial intelligence can build prediction models and classification models to predict future trends of the system and classify new data by learning patterns and patterns in data [86]. This helps anticipate and respond to changes and uncertainties in the system in advance. In terms of anomaly detection, artificial intelligence can learn the normal behavior pattern of the system and build an anomaly detection model to detect and identify abnormal behaviors in the system [87]. This helps to promptly detect and resolve abnormalities in the system and improve system stability and security. In terms of optimization and decision-making, artificial intelligence can learn the dynamics and objective functions of the system to find optimal strategies and decisions. This can be used to solve optimization problems and decision-making problems, improving the efficiency and performance of the system [88].
In summary, the application of artificial intelligence in mathematical modeling of complex systems [illegible] application value [89]. Through techniques such as machine learning and deep learning, artificial intelligence can learn from large amounts of data and discover patterns and laws in the system [90], providing powerful tools and methods for the modeling and analysis of complex systems. This will provide new ideas and methods for understanding and solving problems in complex systems and promote the research and application development of complex systems.

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Conflict of Interest
The author declares there is no conflict of interest regarding this paper.

Data Availability Statement
There is no data associated with this paper.

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