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ORIGINAL

Feedback Delay of Aerobics Intelligent Learning System Based on Model Predictive Control and Artificial Intelligence

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Abstract

In order to improve the operation effect of aerobics intelligent learning system, this paper applies fuzzy predictive control and artificial intelligence technology to system optimization to analyze the unified modeling, stability analysis and controller design of the network control system under the influence of time delay and packet loss. Moreover, this paper establishes the relationship between delay characteristics (time-varying and containing upper bounds) and packet loss characteristics (random and maximum allowable packet loss rate) and the performance of the network control system to construct an aerobics intelligent learning system. In addition, this paper analyzes the functional structure of the system and proposes an aerobics intelligent learning system based on fuzzy control prediction and artificial intelligence. Finally, this paper designs experiments to verify the system proposed in this paper. Through experimental research, it can be known that the system proposed in this paper has certain practical effects.

Keywords. Model predictive control, artificial intelligence, aerobics, intelligent learning, feedback delay

1. INTRODUCTION

The 21st century is a century of rapid development of information, and human society has entered a prosperous information age. The total amount of knowledge has increased sharply. As an extension of education informatization, online education in my country's colleges and universities is developing rapidly, and it is getting more and more attention from the education circle. At present, my country's university network education has penetrated into many disciplines. At the same time, physical education and aerobics teaching should also conform to the development of network education in universities and accelerate the development of physical education and aerobics network teaching. In addition, its research needs to form a multi-channel teaching pattern, optimize physical education and aerobics teaching, and continuously improve its quality (Al-Musawi et al., 2020).

In many systems in real life, such as network systems, biological systems, computer systems, logistics systems, power systems, etc., due to the complexity and variability of the system, traditional central control decision-making cannot well realize people's expected functions. At this time, the widely adopted control strategy is to decentralize these large systems into many small systems, and realize overall planning through decentralized control. Each individual does not need to know the overall information, but only needs to adjust his posture by obtaining the information of the individuals who have a certain connection with him, so as to realize the overall goal planning. The research of distributed control system has a long history and has received wide attention from various fields, such as biology, physics, computer, control and so on. Moreover, each individual in a distributed system is called an agent, and the entire system constitutes a multi-agent system (Bui et al., 2020).

The research process of multi-agent distributed system faces many difficulties in practical applications. For example, first, the information interaction between multiple agents in a multi-agent system makes its dynamics more complicated than that of a single agent. The actual design and implementation need to comprehensively consider the performance of a single agent and the entire network topology, and also need to give a qualitative analysis of the stability of the entire system. Second, agents are physically uncoupled, but their behaviors are coupled to complete a complex task together. Although task decomposition and distribution have been well resolved in traditional centralized control methods, distributed multi-agent systems are coupled between subgroups. However, how they overcome the problem of computational complexity has not been clearly explained, Third, the communication link between agents is not ideal. Even if the current communication network can provide a complete information exchange platform, the controller may not work properly due to the limitation of communication bandwidth, packet loss, and uncertain communication link connectivity. Fourth, when the multi-agent system interacts with information, since the information transmission takes time, it is inevitable that the signal obtained by the system is not a real-time signal, and the processing of the signal also takes time. How to study the impact of these delays on the system is also an important issue (Chapi et al., 2017).

Congestion often tends to worsen. If a router does not have enough buffer space, it will discard newly arrived packets, but when these packets are discarded, the source node that sends these packets will retransmit these packets, and may even retransmit multiple times (Chou & Bui, 2014). This will cause more packets to enter the network and be discarded by routers in the network. It can be seen that the retransmission caused by congestion will not alleviate the network congestion, but will make a vicious circle and aggravate the network congestion. Therefore, how to find a suitable congestion control algorithm to avoid congestion has become an important topic accompanying the development of the network (Yaseen, El-Shafie, Jaafar, Afan, & Sayl, 2015; Zappone, Di Renzo, Debbah, Lam, & Qian, 2019).

There are two main types of congestion control algorithms in the Internet. One is the TCP congestion control algorithm that is applied to the source node and adjusts the data transmission window based on the network congestion signal. The other is the active queue management algorithm (AQM) (Enshaei, Robson, & Edmondson, 2015), which is applied to the network connection node, when the network is overloaded to determine how the network discards the arriving packets. The current congestion avoidance and flow control algorithms used by Internet network terminals are mainly based on the window control algorithm TCPRcno and its deformation algorithm proposed by Bui (Ferrari et al., 2019). The research results show that only relying on the TCP congestion control algorithm of the source node cannot guarantee the reliable transmission of the network, and the queue management algorithm of the connection node also seriously affects the performance of the network. Therefore, the connection node should also adopt an active queue management algorithm to effectively avoid the occurrence of congestion (Laird, Lebiere, & Rosenbloom, 2017). At present, the congestion control algorithm used at the connection in the network is mainly the drop tail method (Ghahramani, 2015). However, this method has drawbacks. The recommended connection node of RFC2309 mainly adopts the random early detection (RED) congestion control algorithm proposed in the literature (Hashemi, Spaulding, Shaw, Farhadi, & Lewis, 2016). This algorithm is also the main active queue management strategy adopted by connection nodes in the Internet.

The Internet Recommendation RFC2571 defines four algorithms for congestion control, namely slow start(Hashemi et al.2016), congestion avoidance (Lu, Li, Chen, Kim, & Serikawa, 2018), fast retransmission (Pham et al.2019) and fast recovery (Nourani, Baghanam, Adamowski, & Kisi, 2014). The so-called fast recovery means that if a node receives an out-of-sequence segment, and it immediately sends an ACK for the last received in-sequence segment. For each subsequent segment, TCP continues to send this segment repeatedly until it receives the missing segment to correct the out-of-sequence packet, and then TCP sends the last accumulated ACK. The fast recovery strategy is that when TCP detects the loss of data packets, the maximum threshold of the source setting window is half of the current congestion window, and the network adjusts the sending window size according to the law of slow start and congestion avoidance (Pham et al., 2019).

After years of development, the current TCP protocol mainly includes four versions (Sustrova, 2016): TCPTahoe, TCPReno, TCPNewReno and TCPSACK. TCPTahoe is an early version of TCP. It includes the three most basic stages of congestion control: slow start, congestion avoidance and fast retransmission. TCPReno adds a "fast recovery" phase on the basis of

TCPTahoe (Sun, Young, Liu, & Newman, 2018). TCPNewReno revises the "fast recovery" phase in TCPReno, which takes into account the loss of multiple data packets within a sending window. In the Reno version, the sender exits the "quick recovery" phase after receiving a new ACK, while in the NewReno version, it exits the "quick recovery" phase only after all data packets are confirmed. TCPSACK is also concerned with the loss of multiple data packets in a window. It avoids the situation that the previous version of TCP retransmits all data message segments in a window, including those data message segments that have been correctly received by the receiving end. It just retransmits the discarded data segments.

2. Objectives

This paper studies aerobics intelligent learning system, and combines model predictive control and artificial intelligence technology to analyze the system's feedback delay to improve system performance.

3. METHODOLOGY

3.1 Modeling of Network Control System

Figure 1 shows the structure of the network control system studied in this article:

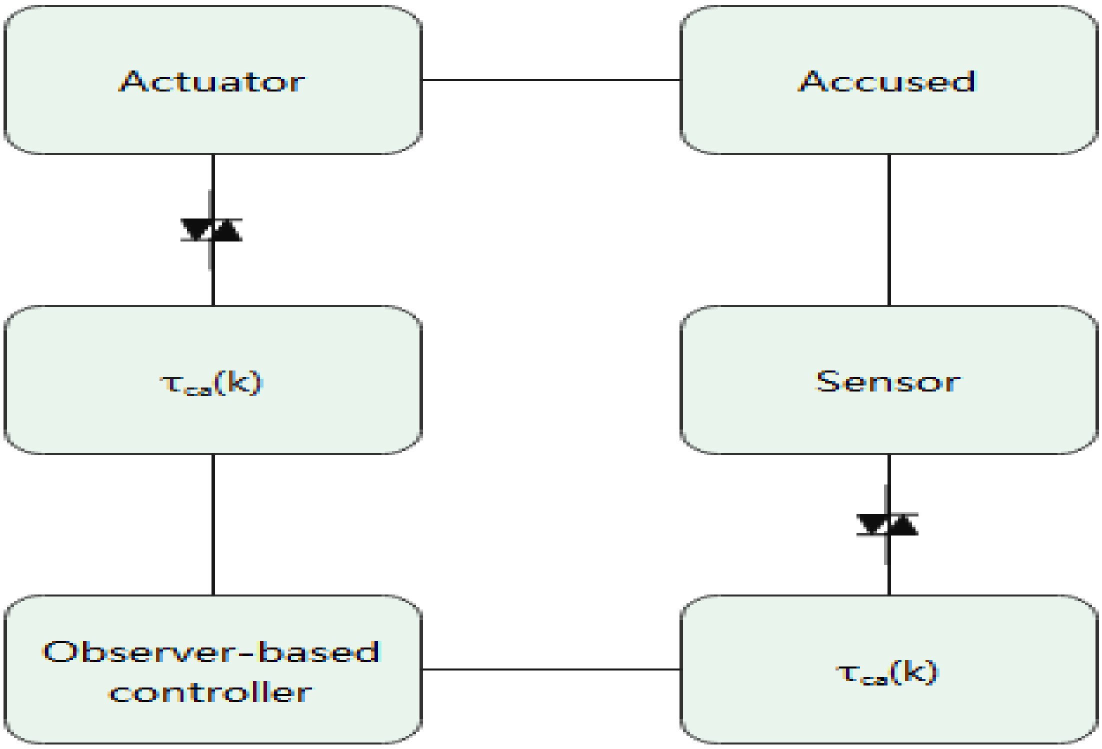

Figure 1. Structure diagram of a network control system with random packet loss and short delay

Hypothesis 1: The global clock is synchronized.

Hypothesis 2: τ_{sc} and τ_{ca} are used to represent the time delay between

S-C and C-A respectively, and the time delay satisfies: $\tau_{sc} < T$, $\tau_{ca} < T$.。

Hypothesis 3: The controller and actuator nodes both adopt a keep-input strategy, that is, when data packet loss occurs, the controller and the actuator keep the data information at the previous moment.

As shown in Figure 1. S_1 and S_2 respectively represent the data packet loss of the two channels. For example, when S_1 is closed, it means that there is no data packet loss from the controller to the actuator, that is, $v(k)$ is smoothly transmitted to the actuator, *u(k)=v(k)*.

On the contrary, if S_1 is disconnected, that is, C-A has data packet loss, and the actuator keeps the input of the previous state, then $u(k) = u(k-1)$. Similarly, for S-C, when S_2 is closed, w(k)=y(k). When S_2 is disconnected, w(k)=w(k-1).

α and *β* indicate the status of S_1 and S_2, and *α*=0(*β*=0) indicates that S_1(S_2) is closed, that is, there is no data loss in the channel. On the contrary, α=1 (β=1) means that S_1（S_2） is disconnected, and the channel has data packet loss.

At time k, the sensor and controller respectively transmit *y(k)* and *v(k)* to the network. In Hypothesis 1, it has been defined that both the controller and the actuator adopt the time-driven mode. Therefore, even though a data packet arrives, the controller and actuator do not act.

The state error variable is defined:$e(k) = x_P(k) - \hat{x}(k)$, and the augmented state variable is denoted as:

$$x(k) = [x_p^T(k)\ e^T(k)\ u^T(k-1)\ w^T(k-1)]^T \quad (1)$$

Based on the above analysis, the closed-loop network control system model with random packet loss and short delay can be modeled as follows:

$$x(k+1) = \Phi i x(k) \qquad (2)$$

Among them,

$$\Phi_i = \begin{bmatrix} A+(1-\alpha)BK & -(1-\alpha)BK & \beta B & 0 \\ \beta LC & A-LC & 0 & -\beta l \\ (1-\alpha)K & -(1-\alpha) & \alpha I & 0 \\ (1-\beta)C & 0 & 0 & \beta I \end{bmatrix} (3)$$

i=1,2,3,4, α∈ {0,1},β∈ {0,1}

That is, the closed-loop system has the following four subsystems:

(1) When α=0, β=0, that is, when there is no data packet loss in both channels:

$$x(k+1) = \Phi_1 x(k) \qquad (4)$$

$$\Phi_1 = \begin{bmatrix} A+BK & -BK & 0 & 0 \\ 0 & A-LC & 0 & 0 \\ K & -K & 0 & 0 \\ C & 0 & 0 & 0 \end{bmatrix}$$

(2) When α=0, β =1, that is, packet loss only occurs in the case of S-C:

$$x(k+1) = \Phi_2 x\,(k) \qquad (5)$$

$$\Phi_2 = \begin{bmatrix} A+BK & -BK & 0 & 0 \\ LC & A-LC & 0 & -L \\ K & -K & 0 & 0 \\ 0 & 0 & 0 & I \end{bmatrix}$$

(3) When α=0, β=0, that is, data packet loss occurs in the case of C-A:

$$x(k+1) = \Phi_3 x\,(k) \qquad (6)$$

$$\Phi_3 = \begin{bmatrix} A & 0 & B & 0 \\ 0 & A-LC & 0 & 0 \\ 0 & 0 & I & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

(4) When α=1, β=1, that is, when data packet loss occurs in S-C and C-A at the same time:

$$x(k+1) = \Phi_4 x\,(k) \qquad (7)$$

$$\Phi_4 = \begin{bmatrix} A & 0 & B & 0 \\ LC & A-LC & 0 & -L \\ 0 & 0 & I & 0 \\ 0 & 0 & 0 & I \end{bmatrix}$$

Taking into account the random packet loss that occurs on S-C and C-A, the closed-loop network control system (3.4) is modeled as a Markov jump linear system with four modes:

$$x(k+1) = \Phi_{\theta(k)} x(k) \qquad (8)$$

The θ(k) = 1, θ(k) = 2, θ(k) = 3 and θ(k) = 4 of the Markov chain correspond to the four subsystems of the Markov jump linear system. π={πij} represents the transition probability matrix of Markov chain $\theta(k)$, where π_{ij} is defined as:

$$\pi_{ij} = P\{\theta(k+1) = j|\theta(k) = i\} \qquad (9)$$

Among them, $\pi_{ij} \geq 0$, ∀i, j∈I, and satisfy $\sum_{j=1}^{4} \pi ij = 1$. The definition of the state transition matrix is as follows:

$$\pi = \begin{bmatrix} \pi_{11} & \pi_{12} & \pi_{13} & \pi_{14} \\ \pi_{21} & \pi_{22} & \pi_{23} & \pi_{24} \\ \pi_{31} & \pi_{32} & \pi_{33} & \pi_{34} \\ \pi_{41} & \pi_{42} & \pi_{43} & \pi_{44} \end{bmatrix} (10)$$

Under the condition of state i, the conditional probability $\pi_{ij}^{(k)}$ = P{θ(n+k) = j|θ(k) = i} i, j∈S, n≥ 0,k≥ 1 of {θ(k), k∈S} to reach state j at n+k after k-step transition at n is {θ(k).

The matrix $\pi^{(k)}(n) = (\pi_{ij}^{(k)}(n))$ with $\pi_{ij}^{(k)}(n)$ as the i-th row and j-th column is the k-step transition probability matrix when {θ(k), k∈S} in n.

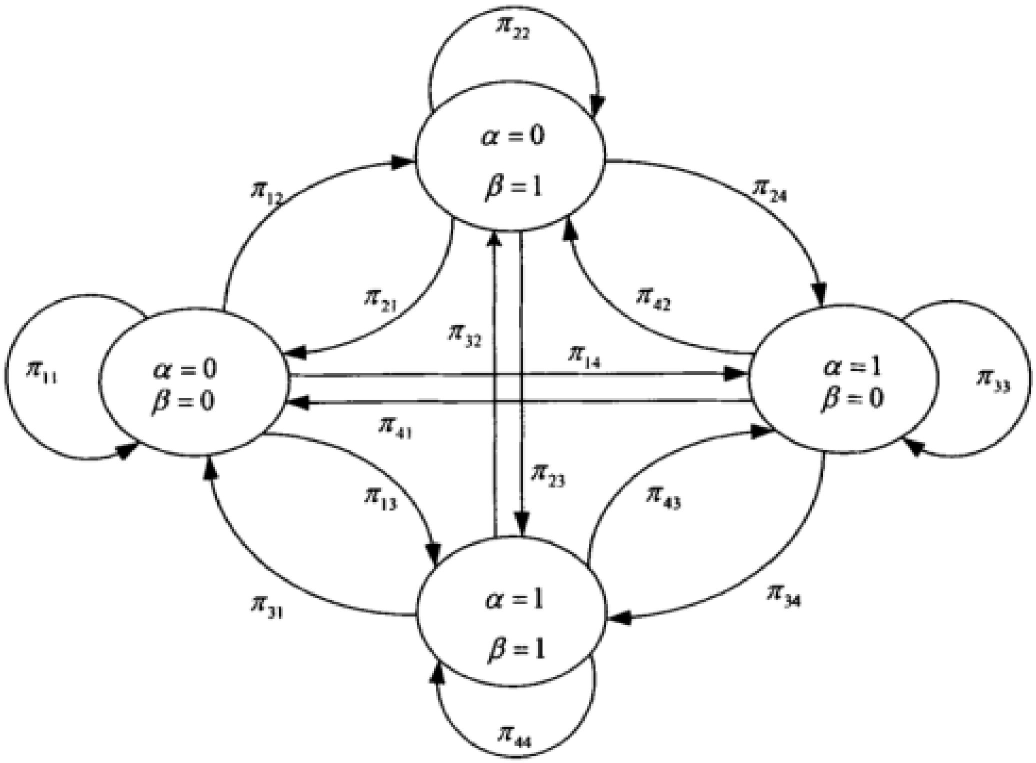

Figure 2. State transition diagram of Markov chain

The closed-loop system is a Markov jump linear system. The data packet loss process between the network control system S-C and C-A is described here. Therefore, the following uses the theory of stochastic systems to analyze and study this type of network control system.

At each sampling moment, the actuator reads the arrived controller output and immediately sends an ACK signal to notify the controller whether it receives the current controller output signal. The observer of the controller can then select which controller output is actually used by the actuator based on this information. Because of this situation, it is difficult to ensure that the observer's input μ(κ) is the same as the final control signal on the object. If this happens, the following form of dynamic output feedback controller can be used:

$$\begin{cases} \hat{x}(k+1) = F\hat{x}(k) + Gw(k) \\ v(k) = H\hat{x}(k) \end{cases} \tag{11}$$

If there is a constant C that makes

$$\sum_{k=0}^{\infty} E\{\|x(k)\|^2 \mid (x_0, \theta_0)\} \le C\Gamma\ (x_0, \theta_0) \qquad (12)$$

hold, where $\Gamma\ (x_0, \theta_0 \ge 0$ is a non-negative function, and the initial state value of the system satisfies Γ (0, . . . , 0)=0, then the system (9) is stochastically stable.

If there is a matrix $P_i > 0$, the matrix inequality

$$\begin{bmatrix} -P_1^{-1} & 0 & 0 & 0 & \sqrt{\pi_{i1}}\Phi_1 \\ * & -P_2^{-1} & 0 & 0 & \sqrt{\pi_{i2}}\Phi 2 \\ * & * & -P_3^{-1} & 0 & \sqrt{\pi_{i3}}\Phi 3 \\ * & * & * & -P_4^{-1} & \sqrt{\pi_{i4}}\Phi 4 \\ * & * & * & * & -P_i \end{bmatrix} < 0 \qquad (13)$$

Holds for all {i, j)$\in l$, then the system (6) is stochastically stable. Among them, Φ_1, Φ_2, Φ_3 and Φ_4 are as defined in systems (2), (3), (4) and (5) respectively.

Prove: For the closed-loop system (9), the following random Lyapunov function is selected:

$$V(k) = X^T(k)P_{\theta(k)}x(k) \qquad (14)$$

The trajectory along the system includes:

$$E[\Delta V(k)]$$

$$= E[V(k+1),\theta(k) - V(k,\theta(k))]$$

$$= E\{x^T(k+1)P_{\theta(k+1)}x(k+1)\} - x^T(k)P_{\theta(k)}x(k)$$

$$= x^T(k)(\Phi_i^T \sum_{j=1}^{4} \pi ij\ P_j\Phi_i - P_i)x(k)$$

$$= x^T(k)\Omega_i x(k) \quad (15)$$

According to Schur's supplementary lemma, it is equivalent to Ωi<0, so:

$$E[\Delta V(k)] \le -\lambda_{min}(-\Phi_i)x^T(k)x(k) \qquad (16)$$

$\le -\gamma x^T(k)x(k)$

Among them, $\lambda_{min}(-\Phi_i)$ represents the smallest characteristic root of $-\Phi_i$, and γ=inf{$\lambda_{min}(-\Phi_i)$}.

From formula (12), it can be obtained that for any t> 0,

$$E[V(k+1)] - E[V(0)] \le -\gamma \sum_{k=0}^{t} E\ [x^T(k)x(k)] \qquad (17)$$

Furthermore, we obtain: $\sum_{k=0}^{t} E\ [\ x^T(k)x(k)] \le \frac{1}{\gamma} E[V(x_0,\theta_0)]$

When t→∞, we obtain:

$$\sum_{k=0}^{t} E\ [\ x^{T}(k)x(k)] \leq \frac{1}{\gamma}E[V(x_0,\theta_0)]<\infty \qquad (18)$$

4. Aerobics Intelligent Learning System Based on Fuzzy Prediction and Artificial Intelligence

Moreover, this requires designers to fully consider the long-term development of the system while designing the online education platform, so that the system is conducive to improvement and expansion.

In doing so, we ensure that the system not only supports immediate needs but also lays a robust foundation for future enhancement and growth. The architecture diagram is shown in Figure 3:

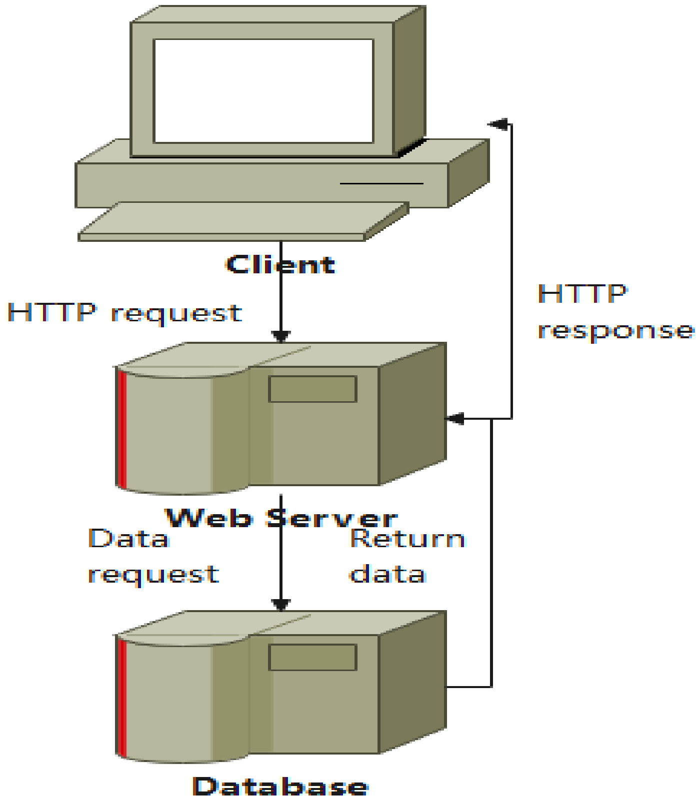

Figure 3. Schematic diagram of the system architecture

The aerobics network course is divided into six modules for design (see Figure 4). They are login and registration module, course introduction module, learning module, communication and Q&A module, examination-related module, and knowledge expansion module. The aerobics learning module consists of six sub-modules: basic knowledge, basic exercises, routine practice, aerobics creation, technical action scoring standards, and basic quality scoring standards. Communication and Q&A include three sub-modules of aerobics course announcements, frequently asked questions, discussion areas, short messages and instant messaging tools. The aerobics test module includes two sub-modules: theory test and score announcement. The development of aerobics knowledge includes three sub-modules: related downloads, excellent aerobics website, and excellent aerobics papers.

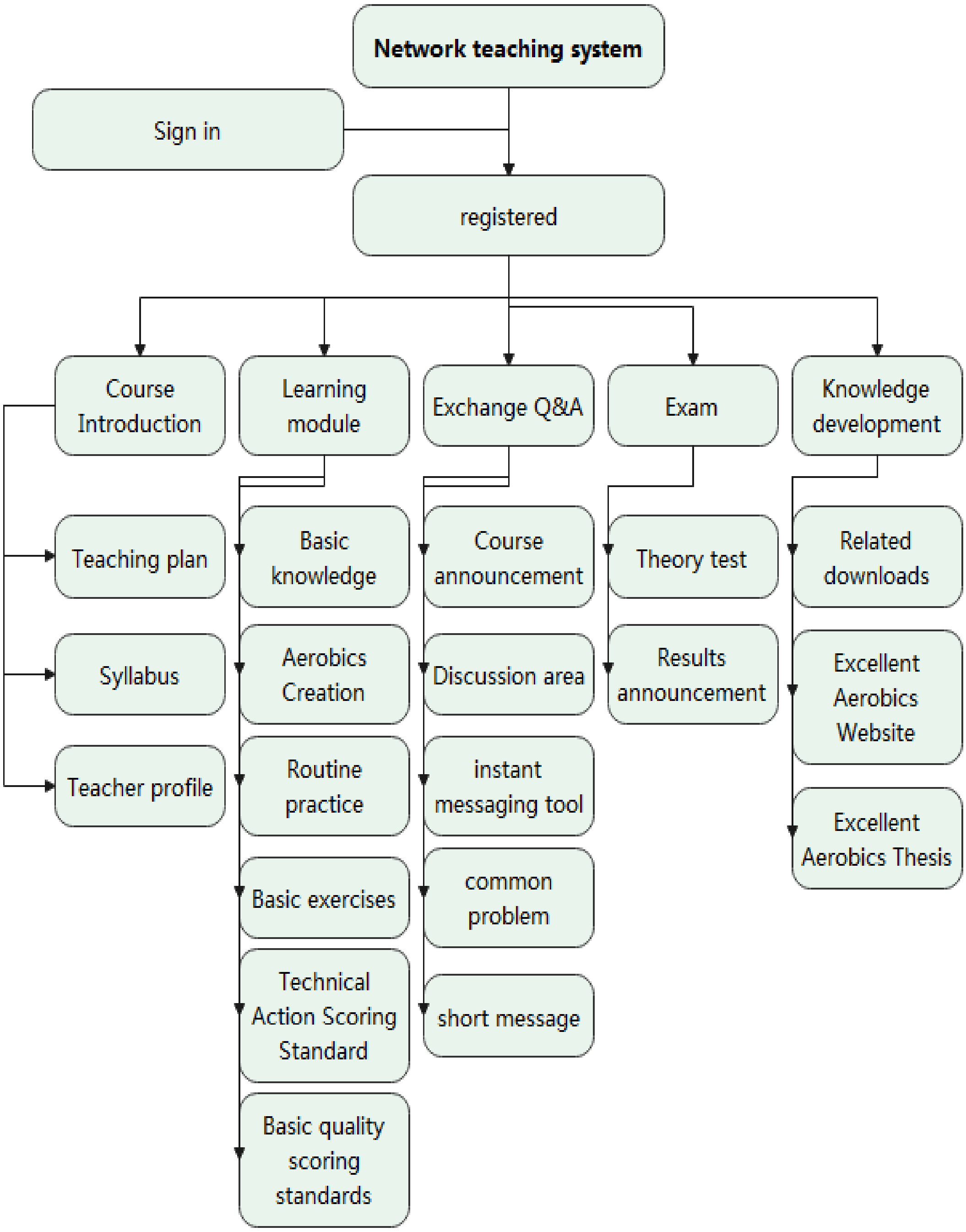

Figure 4. The overall framework of aerobics network teaching system

When entering the aerobics course, the system will prompt to register, which is divided into three types: teacher, administrator, and student. In the entire aerobics online teaching course, different identities will have different operating rights after logging in. Aerobics teachers can upload and modify aerobics courses within a certain range, communicate with students, and answer students' questions. Moreover, aerobics teachers also have the authority of students.

Students can manage their basic registration information. After registering, students can log in to the system to browse and use all the contents and functions of the system. Figure 5 shows the flow chart of different authority browsers entering the aerobics teaching system to learn:

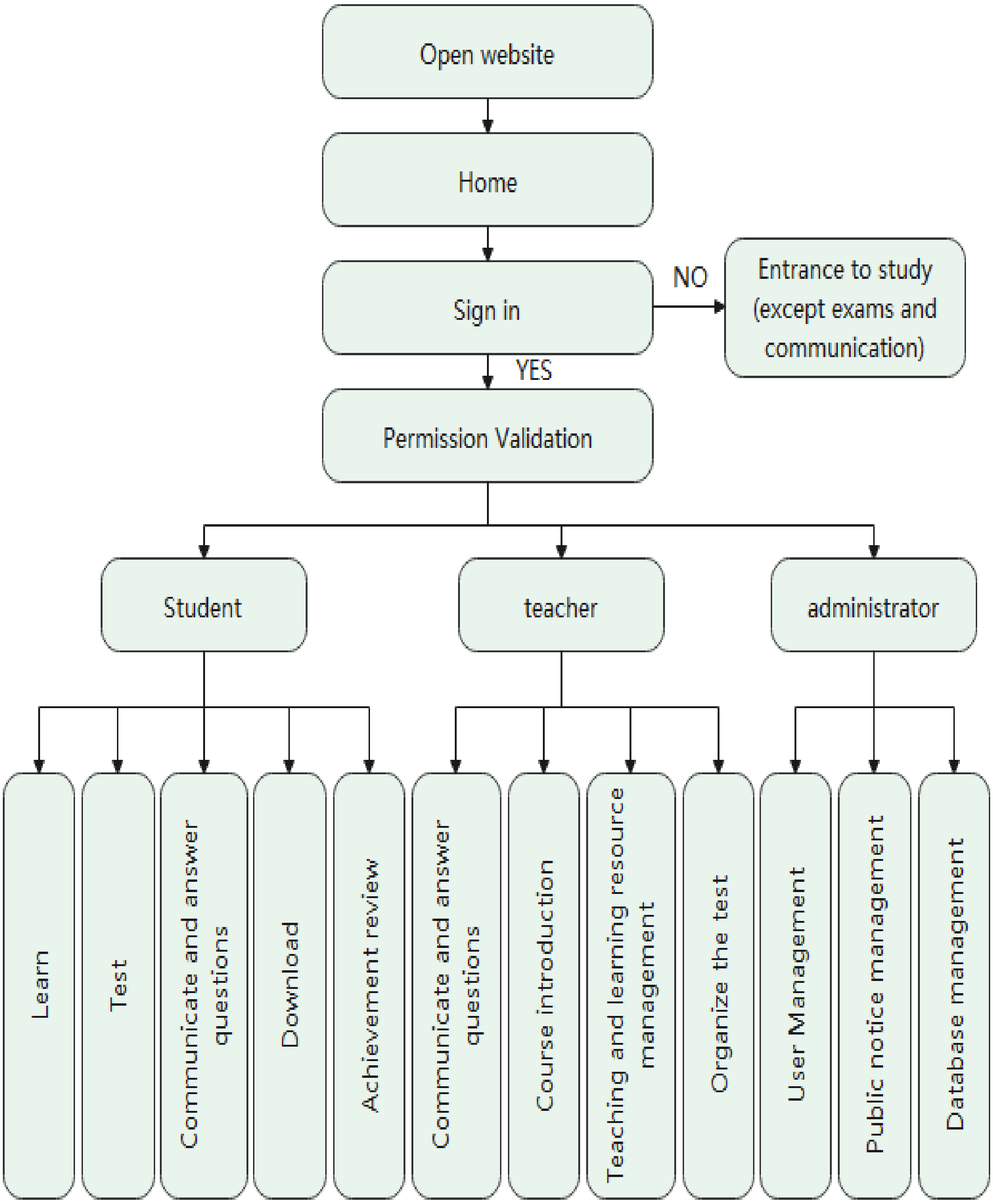

Figure 5. The learning process of the network teaching system

In order to ensure the openness of aerobics courses, login and registration are not mandatory. Learners can browse and learn aerobics courses even if they do not log in to the system.However, students who take exams and answer questions must register and log in. The basic information of students, teachers and administrators of this school has been stored in the database, as shown in Figure 6.

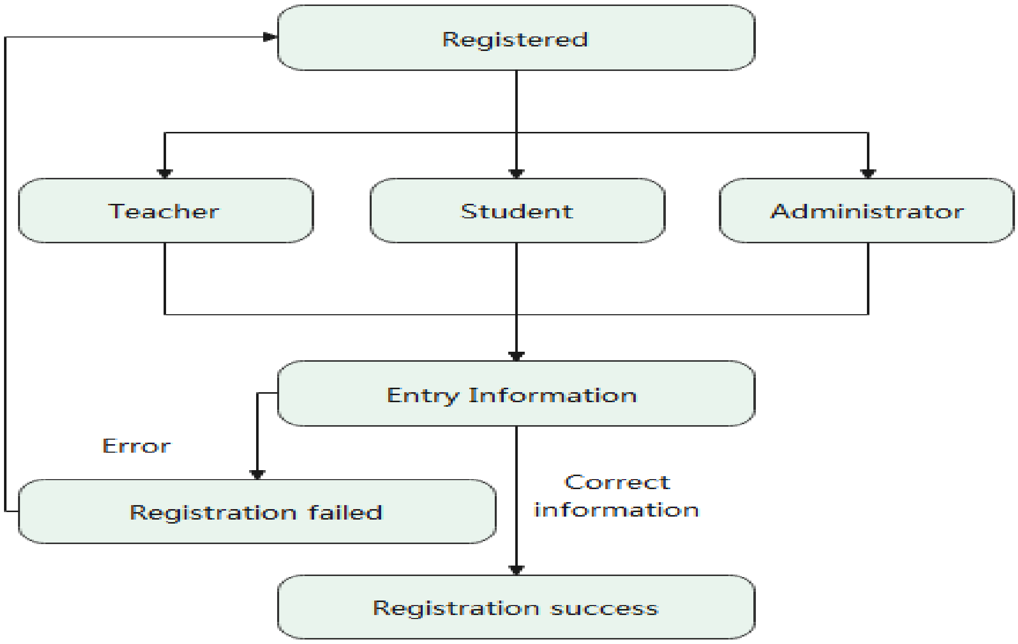

Figure 6. Registration process

After successful registration, users can return to the login module on the upper right corner of the homepage to log in. The user fills in the name and password that he used when registering. If the name and password are filled in correctly, the login is successful. If it is incorrect, the system prompts that the user name or password is incorrect, please log in again. The login process is shown in Figure 7:

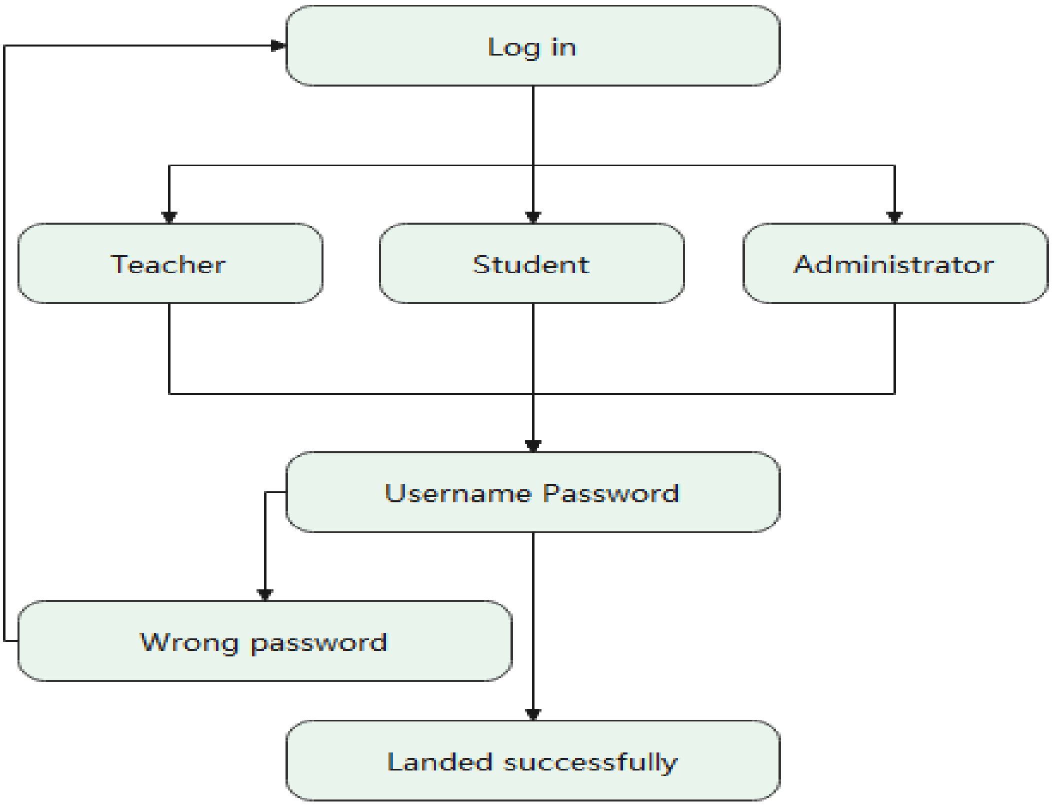

Figure 7. User login process

5. RESULTS

This paper constructs an aerobics intelligent learning system based on fuzzy control prediction and artificial intelligence, and then tests the performance of the system. The feedback delay test is carried out through the algorithm proposed in this paper, and the user satisfaction of the improved system is investigated. This article first verifies the effect of system feedback delay through simulation experiments, and the results are shown in Table 1 and Figure 8.

Table 1. Statistical table of feedback delay effect

NO	System delay	NO	System delay	NO	System delay
1	93.4	25	89.0	49	94.1
2	95.5	26	88.5	50	87.5
3	94.9	27	93.4	51	88.7
4	95.8	28	96.9	52	95.9
5	88.4	29	92.9	53	87.2
6	92.5	30	92.3	54	88.5
7	88.7	31	94.1	55	87.5
8	93.7	32	95.7	56	89.4
9	91.9	33	96.2	57	91.5
10	92.5	34	93.7	58	90.5
11	87.2	35	89.3	59	94.0
12	88.5	36	88.9	60	96.6
13	90.5	37	94.8	61	93.9
14	92.6	38	96.0	62	93.0
15	88.1	39	91.8	63	96.2
16	89.6	40	89.1	64	88.9
17	90.4	41	93.0	65	88.0
18	96.0	42	96.2	66	87.9
19	94.5	43	87.5	67	93.6
20	88.2	44	95.3	68	93.3
21	87.1	45	95.6	69	90.4
22	90.3	46	88.1	70	94.9
23	95.9	47	90.2	71	87.4
24	92.7	48	89.1	72	95.0

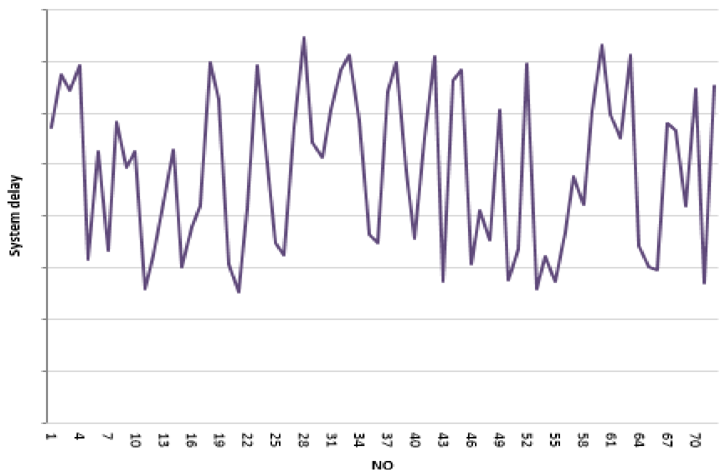

Figure 8. Statistical diagram of feedback delay effect

From the above research, it can be seen that the aerobics intelligent learning system based on fuzzy control prediction and artificial intelligence built in this paper has a good feedback delay effect and can effectively improve the efficiency of the system. On this basis, a system satisfaction survey is conducted, and the results obtained are shown in Table 2 and Figure 9.

Table 2. Statistical table of user satisfaction of the improved system

NO	Satisfaction	NO	Satisfaction	NO	Satisfaction
1	90.3	25	85.2	49	83.1
2	90.7	26	94.7	50	87.9
3	86.5	27	84.9	51	96.9
4	92.5	28	97.2	52	92.0
5	87.0	29	88.9	53	90.0
6	90.2	30	90.2	54	91.0
7	92.5	31	98.0	55	89.2
8	96.2	32	94.7	56	85.5
9	96.2	33	88.1	57	86.1
10	95.6	34	95.6	58	84.2
11	91.2	35	88.1	59	91.8
12	97.4	36	83.4	60	86.6
13	88.7	37	90.1	61	95.7
14	91.5	38	96.9	62	95.6
15	90.8	39	85.0	63	90.8
16	88.5	40	92.3	64	96.0
17	93.1	41	85.3	65	90.6
18	90.6	42	93.8	66	91.2
19	83.7	43	86.6	67	91.5
20	96.7	44	89.4	68	90.1
21	91.3	45	86.4	69	95.0
22	89.9	46	95.4	70	89.6
23	84.5	47	94.4	71	85.6
24	84.9	48	93.8	72	91.6
17	93.1	41	85.3	65	90.6

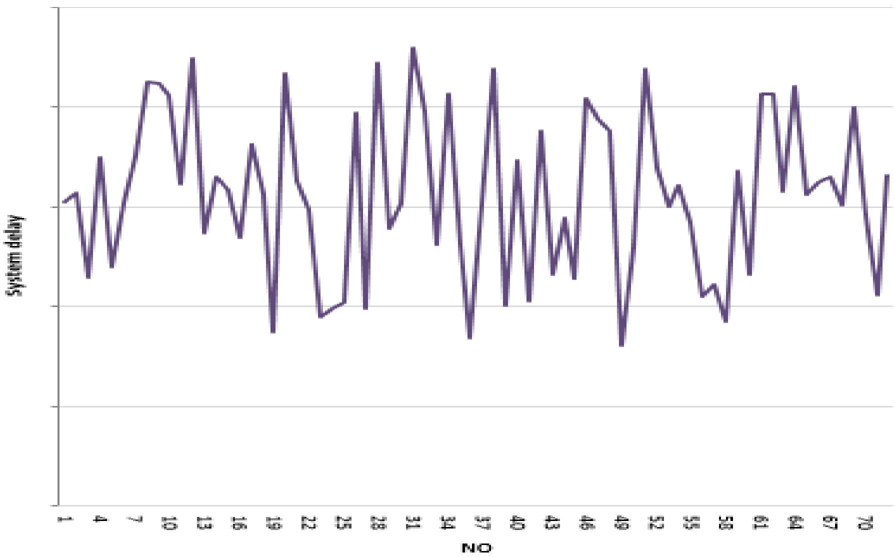

Figure 9. Statistical diagram of user satisfaction of the im-proved system

6. DISCUSSION

It can be seen from the above research that the feedback delay test method of aerobics intelligent learning system based on fuzzy control prediction and artificial intelligence proposed in this paper can effectively improve system performance and increase system user satisfaction.

7. CONCLUSION

Aerobics network teaching is an extended classroom teaching that conforms to the needs of the reform and development of aerobics courses in colleges and universities, and combines classroom teaching with extracurricular self-study. Moreover, it fully mobilizes students' initiative and flexibility through rich teaching resources and diverse teaching methods, and meets the needs of students' individualized learning of aerobics. In addition, it has better promoted the all-round development of aerobics teaching and its students' physical and mental health, which is the direction of the development of modern colleges and universities network teaching. This paper constructs an aerobics intelligent learning system, analyzes the system's functional structure, and proposes a feedback delay system for aerobics intelligent learning system based on fuzzy control prediction and artificial intelligence. Moreover, this article analyzes the unified modeling, stability analysis and controller design of the network control system under the influence of time delay and packet loss. At the same time, the relationship between delay characteristics (time-varying, with upper bounds) and packet loss characteristics (random, maximum allowable packet loss rate) and network control system performance is established. The experimental research shows that the method proposed in this paper is feasible.

8. RECOMMENDATIONS

The system constructed in this paper needs to be further improved in the future work, and the conclusion needs to be verified through more practice.

9. ACKNOWLEDGEMENT

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2. Zhejiang University Education "14th Five-Year Plan" teaching reform project，Project No. is jg20220420 , the title of project is “Teaching reform of art physical education courses in the context of curriculum ideology and politics with the implementation path”.

3. General scientific research project of Zhejiang Provincial Department of Education，Project No. is Y202249144，the title of project is “Exploration and practice of ideological and political integration path in art sports courses”.

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