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Research article

Promoting peer learning in education: Exploring continuous action iterated dilemma and team leader rotation mechanism in peer-led instruction

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Abstract: This paper promotes teacher-guided peer learning in education with continuous action iterated dilemma (CAID) based on team leader rotation mechanism. In previous teaching activity models, the learning communication relationship between peers was described as static, but the static relationship will hinder the learning efficiency, which does not match the real world. In addition, in view of the independence of individual students, it is necessary to establish a dynamic model which considers the complex behavior of every student. In this paper, we first propose a team leader rotation mechanism that makes sure each student has the opportunity to become a team leader, which enhances students' sense of participation and improves classroom efficiency. Next, we establish a multi-layer nonlinear student dynamic model based on continuous action iteration dilemma and involved complex and unknown nonlinear environmental factors to fit different environmental influences on different students. Also, in order to demonstrate the convergence of the proposed model, we devise the Lyapunov function as a means of mathematical proof. Through this analysis, we establish the stability of the proposed model and verify its independence from parameters, thereby enhancing its applicability in practical contexts. By incorporating the team leader rotation mechanism proposed in this paper, teachers will be able to ensure diverse student engagement to achieve information consistency, thereby ensuring the effectiveness of the classroom.

Keywords: teacher-guided peer learning; continuous action iterated dilemma; team leader rotation mechanism; peer learning; Lyapunov method

1. Introduction

Due to the effective improvement of teaching quality in peer learning, it has been widely researched [1–3]. It emphasizes interaction and sharing between students [4]. Students can learn knowledge from their peers, pass on their own knowledge to them, and learn from each other to bring about common progress. It can be seen that the way students communicate with others significantly affects the quality of teaching [5–7] because the lack of communication within the group leads to the inability to form a consensus. In addition, it should be noted that there are large individual differences among students and we need to use a more accurate mathematical model to describe [8–10]. In fact, there are network structures similar to teaching activities in the field of multi-agents, such as [11, 12]. In order to provide better theoretical guidance for teaching activities, we designed a continuous action iteration dilemma peer learning with a team leader rotation mechanism.

Many researchers have conducted research on peer learning [13–16]. Peer learning is an activity different from adversarial differential games. For more about adversarial differential games, one can refer to [17]. So far, existing results only analyze the static connections between students and do not fully take into account the characteristics of different students. When students are sitting in the classroom, the continuous change of communication is more conducive to the improvement of knowledge absorption. Therefore, this paper designs a method of rotating team leaders, in which all students can be called team leaders, thereby enhancing each student's sense of participation and improving the quality of teaching.

For the study of peer learning under the guidance of teachers, the key is to abstract student behavior into a mathematical model [18–20]. In [21], the authors present a method that utilizes survey data analysis to enhance student performance. [22] studies the behavior of students in the presence of noise and gives its mathematical description. The author uses a filtering idea to reduce the impact on student behavior. The authors of [23] used automatic speech recognition technology to obtain data from actual classrooms to constitute imitation of teacher-student behavior. Clearly, current student models lack individual uniqueness in the mathematical modeling process, despite the fact that every student is different in reality. In addition, environmental factors such as teachers can also have an impact on education and teaching, such as random interference in field control theory [24] and actuator and sensor failures [25]. Therefore, it becomes imperative to consider how to incorporate mathematical methods to fit environmental influences. To this end, this paper proposes a CAID-based model to describe external influences.

The main contributions can be summarized into three points:

1) We propose a team leader rotation mechanism and mathematically model it. On the basis of information gathering among students, each student has the opportunity to become a team leader, which enhances students' sense of participation and improves classroom efficiency.

2) Considering that the model may be subject to nonlinear external disturbances, we design the CAID model, which can cope with the external disturbances received by students in the classroom.

3) We propose a model that combines the team leader rotation mechanism and student dynamic model. By employing the Lyapunov function, we demonstrate the convergence and stability of the proposed model, showcasing its resilience to parameter variations. This analysis enhances the model's applicability in various contexts.

The rest of this paper is organized as follows. In Section 2, we present an overview of the model CAID. This section also introduces some key concepts. In Section 3, we model the CAID with external disturbance and team leader rotation mechanism. In Section 4, the stability of the rotation mechanism is taken into account. Section 5 provides a simulation. The obtained results demonstrate the positive outcomes of the model. Finally, in Section 6, the conclusion is presented, summarizing the key findings and implications of the study.

2. Preliminary

In this section, we provide an overview of the fundamental concepts related to the dynamic model of CAID. This knowledge serves as a foundation for understanding the subsequent discussions and analysis in the paper.

2.1. Dynamic model for student based on CAID

First, the definition of peer learning is introduced in this paper as Definition 1.

Definition 1: Peer learning, also known as peer education or peer teaching, is a collaborative learning approach in which individuals of similar age or status engage with each other to share knowledge, skills, information and experiences to facilitate mutual learning and personal development.

The interconnection between students can be denoted by an undirected graph $G = (V, E)$, where $V = v_1, v_2, \cdots, v_m$ denotes the set of students, while $E \in R^{m\times m}$ represents connections between vertices. Note that the existence of a connecting relationship between student v_i and student v_j can be determined by the values of e_{ij}. Specifically, if a connection exists, we have $e_{ij} = 1$, otherwise, $e_{ij} = 0$. We begin by conceptualizing the exchange of information among classmates as a game model. In order to describe the behavior more accurately, we introduce a model called CAID, which serves as a dynamic representation of student behavior in the information exchange process. Let $x_i \in [0, 1],\ i \in \{1, 2, \cdots, m\}$, where x_i represent the strategy students i adopting. Obviously, the value $x_i = 0$ means it is full detection. $x_i = 1$ implies full cooperation.

The evolutionary dynamics are significantly influenced by payoff matrix, which serves as the foundation for students to make choices. The payoff matrix is a crucial determinant in the decision-making process. We select the payoff matrix P as follows:

$$\begin{bmatrix} \lambda_0 & \lambda_1 \\ \lambda_2 & \lambda_3 \end{bmatrix}, \tag{1}$$

where $\lambda_0, \lambda_1, \lambda_2, \lambda_3$ represent the payoffs associated with students utilizing a binary strategy. Therefore, the the strategy fitness $H(x_i)$ can be defined as

$$H(x_i) = \sum_{j=1}^{m} e_{ij}[(\lambda_0 - \lambda_1 - \lambda_2 + \lambda_3)x_i x_j + (\lambda_1 - \lambda_3)x_i + (\lambda_2 - \lambda_3)x_j + \lambda_3]. \tag{2}$$

Obviously, it holds that

$$\Delta H_{ji} = H\left(x_j\right) - H(x_i). \tag{3}$$

According to imitation dynamics, we have

$$x_i(n+1) = \frac{1}{\deg(v_i)} \sum_{j=1}^{m} [\left(1 - s_{ij}e_{ij}\right) x_i(n) + s_{ij}e_{ij}x_j(n)], \tag{4}$$

where n is the number of evolutionary progress and $s_{ij} = sig(\xi|\Delta H_{ji}|)$ is defined as the sigmoid function of ξ multiplied by the absolute difference in the fitness values ΔH_{ji}. The sigmoid function is denoted as $sig(\xi|\Delta H_{ji}|) = 1/(1 + exp(-\xi|\Delta H_{ji}|))$, where ξ is a positive parameter. To put it simply, Eq (4) indicates that during iteration n, a student has a probability of s_{ij} to switch to a neighboring student. Additionally, the term $\deg(v_i) = \sum_{j=1}^{m} e_{ij}$ represents the degree of connectivity for student i, which is the sum of the adjacency matrix elements e_{ij} for that student.

Derivation of x_i can be obtained as

$$\dot{x}_i(t) = \frac{1}{\deg(v_i)}\left[\sum_{j=1}^{m} s_{ij} e_{ij}\left(x_j(t) - x_i(t)\right)\right]. \tag{5}$$

Let $\psi_{ij} = \frac{s_{ij}e_{ij}}{\deg(v_i)}$. Thus, the model (5) can be reformulated as:

$$\dot{x}_i(t) = \sum_{j=1}^{m} \psi_{ij}(x_j(t) - x_i(t)) = \sum_{j=1}^{m} \frac{s_{ij}e_{ij}}{\deg(v_i)}\left(x_j(t) - x_i(t)\right). \tag{6}$$

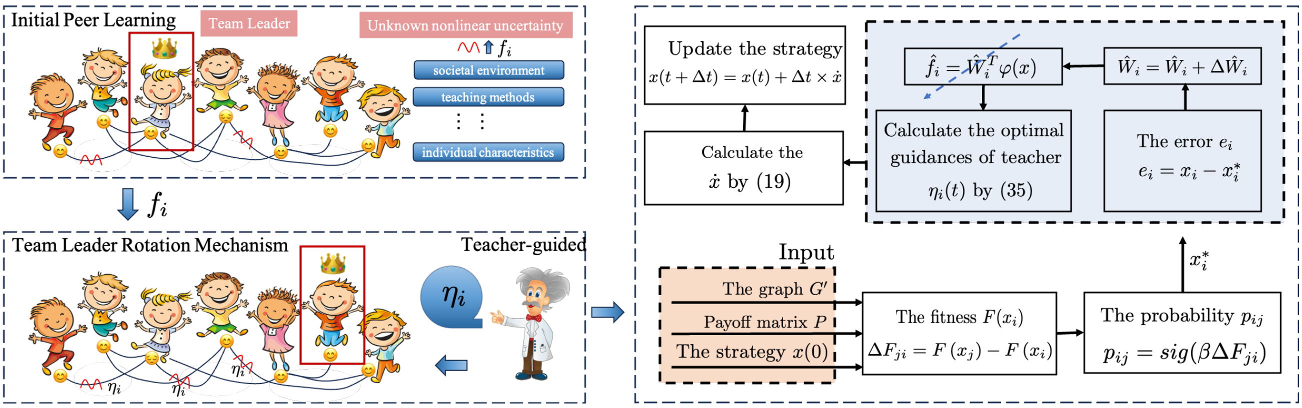


Figure 1. The dynamic model of CAID with teacher-guided peer leaning and team leader rotation mechanism.

3. Model establishment

In this section, we design a CAID model based on the team leadership mechanism considering external disturbance.

3.1. Dynamic model with disturbance

The behavior of students under external interference can be expressed as

$$\dot{x}_i(t) = \sum_{j=1}^{m} e_{ij}\left(\frac{s_{ij}}{\deg(v_i)} + u_i\right)\left(x_j(t) - x_i(t)\right), \tag{7}$$

where u_i represents the influence of complex environment on student i.

3.2. Dynamic model of students with team leader rotation mechanism

Note that the China Unicom network only determines the interactive relationship between students. In addition to the influence of teachers on students' behavior and thinking, the team leader also played an important role. Serving as a group leader can cultivate students' organizational and management skills very well and build a bridge of communication between students and teachers. Therefore, being a group leader of a student group is what many students hope for. But at the same time, there are only a few group leaders in a student group. Always letting a fixed student serve as the group leader will also bring some problems, such as reducing the enthusiasm and participation of the rest of the students. Therefore, it is necessary to establish a team leader rotation mechanism. Based on this, this paper first introduces the dynamic model of the group leader as

$$\dot{x}_I = \sum_{j=1}^{m} \frac{s_{Ij}e_{Ij}}{\deg(v_I)} \left(x_j(t) - x_I(t)\right). \tag{8}$$

where I represents the team leader and $p_{Ij} = min(p_{1j}, \cdots, p_{mj})$. Other students are updated based on (6). The main consideration of setting the dynamics of the group leader to (8) is to highlight the leadership and decision-making role of the group leader. Therefore, when the student served as the group leader, he tried his best to stick to his point of view and reduce the interference of other students' strategies on him.

Then, the important question is how to choose the team leader. We analyze from the characteristics of the team leader. The most important responsibility of the team leader is to coordinate the relationship between the team members. Based on this principle, we set the student with the highest cooperation rate at the current moment as the team leader, but because the status of the students exists uncertain influencing factors, the concept of cooperation is constantly changing. Therefore, we rotate team leaders based on the real-time changes in the cooperation rate of students. Every student has the opportunity to become a team leader to promote the sense of participation and cooperation among students.

4. Convergence analysis

In this part, in order to analyze the convergence of the models which have been introduced, Lyapunov method is employed.

4.1. Convergence analysis of CAID with team leader rotation mechanism

Consider the following system (6)

$$\dot{x}(t) = -L_k x(t), \tag{9}$$

where $L_k = \mathcal{L}(G_k)$ is the Laplacian of graph G_k the belongs to a set Γ and calculated by (10).

$$l_{k,ij} = \begin{cases} \sum_{j=1,j\neq i}^{n} \psi_{k,ij}, & j = i, \\ -\psi_{k,ij}, & j \neq i, \\ \sum_{j=1,j\neq I}^{n} \psi_{k,Ij}, & j = i, \\ -\psi_{k,Ij}, & j \neq I = i. \end{cases} \tag{10}$$

Let α be the equilibrium point of the dynamic model. The distance between x and α, which is denoted as h, represents the error

$$x(t) = \alpha + h. \tag{11}$$

Obviously, it follows that $\dot{\alpha} = 0$. Consequently, we can derive the derivative of h based on Eq (11).

$$\dot{h} = \dot{x}(t). \tag{12}$$

Thus,

$$\dot{h}_i = \dot{x}_i(t) = \sum_{j=1}^{m} \psi_{ij}^{l}(h_j - h_i), \tag{13}$$

where $\psi_{ij}^{l} = s_{ij}^{l} e_{ij} / \deg(v_i)$. Let V be

$$V = \sum_{i=1}^{N} \frac{1}{2} h_i^2, \tag{14}$$

where $\dot{h}$ is derived by (13). Subsequently, the derivative of V can be obtained

$$\dot{V} = -\sum_{(i,j)\in G_k} (h_j - h_i)\psi_{max}^{l}(h_j - h_i)] \leq 0. \tag{15}$$

Thus, the proof is concluded, establishing the convergence of the dynamic model for CAID with a team leader rotation mechanism.

4.2. Convergence analysis of CAID with external disturbance

However, in the case of the dynamic model presented in Eq (7), it is evident that the definition of error as stated in Eq (12) is not satisfied, rendering the calculation of Eq (11) infeasible. In order to ensure that the mentioned model effectively enhances the level of cooperation while maintaining system convergence, we redefine the error for student i as

$$h_i = x_i(t) - x_i^{\star}, \tag{16}$$

where, $x_i^{\star}$ represents the strategy value which have maximum fitness. Hence, we get

$$\dot{h}_i = \dot{x}_i(t). \tag{17}$$

In particular, if the relationship of all students is completely connected, then it can be deduced that $x_1^{\star} = x_2^{\star} = \cdots = x_N^{\star}$. This implies that

$$h_i - h_j = x_i(t) - x_i^{\star} - x_j(t) + x_j^{\star} = x_i(t) - x_j(t). \tag{18}$$

Theorem 1. *Let the weight matrix W is bounded and the communication digraph be strongly connected. Select the optimal guidances of teacher $\delta_i(t)$ as*

$$\delta_i(t) = \arg\min_{\xi}[s_{ij}^{\xi} - s_{ij} + deg(v)\bar{f}]. \tag{19}$$

Denote tuning law as

$$\dot{\hat{W}}_i = \phi(x)\sum_{j=1}^{N} h_i w_{ij}(h_j - h_i). \tag{20}$$

Then, the behavior of system (7) exhibits convergence.

Proof: Let the Lyapunov function be the form of

$$V = \sum_{i=1}^{m}\frac{1}{2}h_i^2 + \frac{1}{2}\hat{W}_i^T\hat{W}_i, \tag{21}$$

where $\hat{W}_i$ denotes the deviation in estimation for student i.

Thus, one can derive the derivative

$$\dot{V} = \sum_{i=1}^{m} h_i\dot{h}_i + \sum_{i=1}^{m}\hat{W}_i^T\dot{\hat{W}}_i. \tag{22}$$

Substitute $\dot{h}_i = \dot{x}_i = \sum_{j=1}^{m} e_{ij}(\frac{s_{ij}^{\xi}}{\deg(v_i)} + u_i)(h_j - h_i)$ into (22), it leads to

$$\dot{V} = \sum_{i=1}^{m}\sum_{j=1}^{m} h_i e_{ij}(\frac{s_{ij}^{\xi}}{\deg(v_i)} + u_i)(h_j - h_i) + \sum_{i=1}^{m}\hat{W}_i^T\dot{\hat{W}}_i. \tag{23}$$

When (19) is satisfied, it can be obtained that

$$s_{ij}^{\xi} \approx s_{ij} - deg(v_i)\bar{f}_i. \tag{24}$$

Therefore,

$$\dot{V} = \sum_{i=1}^{m}\sum_{j=1}^{m} h_i w_{ij}(\frac{s_{ij}}{\deg(v_i)} + \zeta)(h_j - h_i) + \sum_{i=1}^{m}\sum_{j=1}^{m} h_i e_{ij}\hat{W}_i^T\phi(x)(h_j - h_i) + \sum_{i=1}^{m}\hat{W}_i^T\dot{\hat{W}}_i. \tag{25}$$

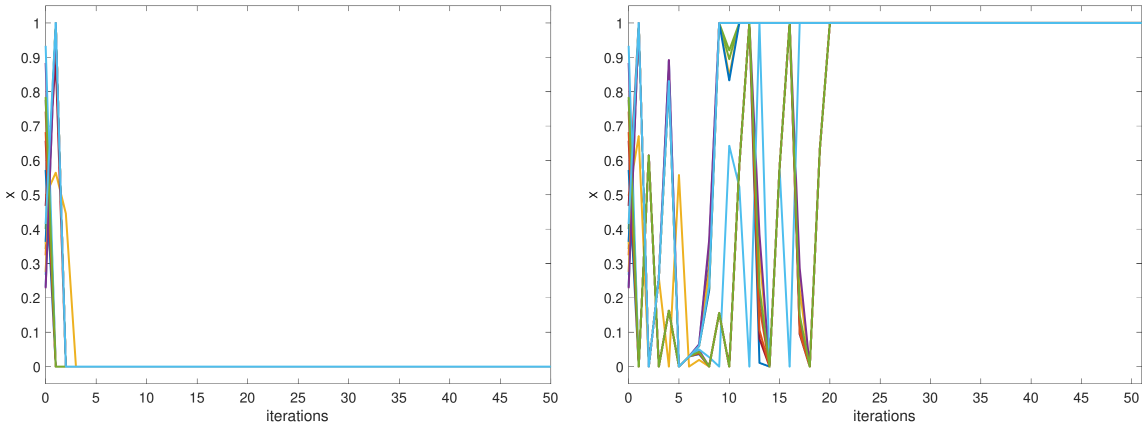
Note that if the tuning law described in Eq (20) is fulfilled, it can be inferred that the derivative $\hat{W}_i$ is given by

$$\hat{W}_i = -\phi(x)\sum_{j=1}^{N} h_i a_{ij}(h_j - h_i). \tag{26}$$

Define $\psi_{ij}^{\xi} = a_{ij}\frac{p_{ij}+deg(v_i)\varepsilon}{deg(v_i)}$, we can get

$$\dot{V} \le -\sum_{i=1}^{N}\psi_{max}(h_j - h_i)^2 \le 0. \tag{27}$$

Consequently, the proof is completed, demonstrating the convergence of the proposed dynamic model (7) for CAID.



(a) $N = 20$, no teacher-guided fully connected network with team leader rotation mechanism

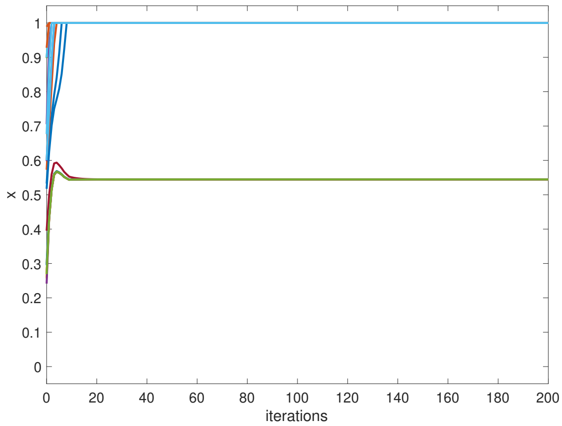
(b) $N = 20$, no teacher-guided fully connected network with team leader rotation mechanism

Figure 2. The convergence for CAIPD.

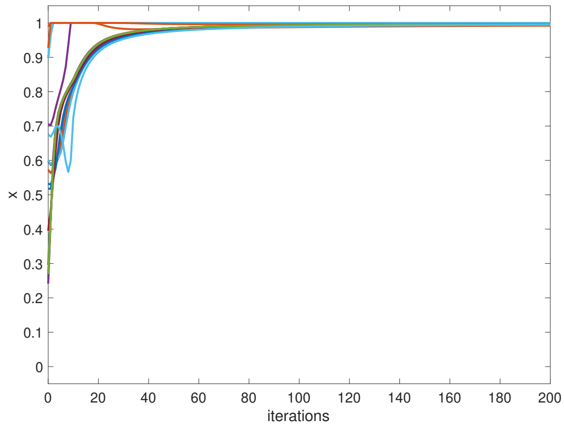
5. Simulation

In this section, a series of experiments are conducted to validate the effect of the mentioned model. If there are disagreements or misunderstandings among students, it can lead to confusion and communication barriers, thus hindering the learning process. Peer learning is typically aimed at achieving common learning objectives. If students have different interpretations of these objectives, it can result in an unclear direction of the learning process or even deviation from the intended learning goals. Therefore, we theoretically validated the proposed peer learning model. In this section, we will validate it further based on experimental data after ensuring that student states have achieved consistency.

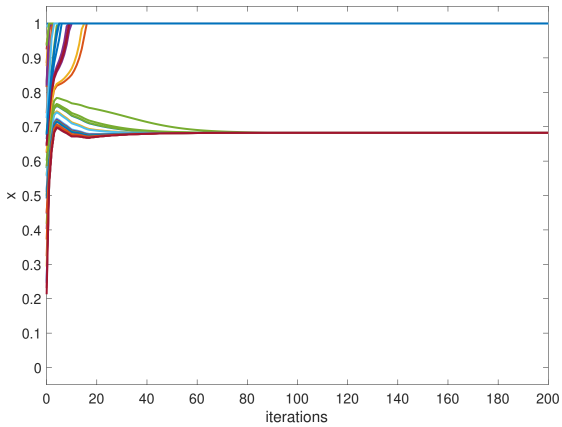
We first generate a fully connected graph G with $N = 20$ students. Next, the performance of the CAID model on G and G' are respectively revealed. The parameters of CAID are set to $p = 5, q = 1, \xi = 1$. From Figure 2(a), it can be seen that the dynamic model without the guidance of the teacher, with the change of team leader and the learning among team members, the final convergence strategy is betrayal. After the proposed teacher-guided peer learning, the result of high cooperation rate as shown in Figure 2(b) is obtained, which proves that teacher-guided peer learning can make students with a team leader rotation mechanism more efficient which is good for teamwork. From Figure 3(a), it can be seen that students cannot reach a consensus with each other as the team leader changes and the learning among team members without the guidance of the teacher. After the proposed teacher-guided peer learning, the result of high cooperation rate as shown in Figure 3(b) is obtained, which also proves that teacher-guided peer learning can make students with a team leader rotation mechanism trend towards better teamwork. At the same time, in order to prove the effectiveness of the proposed method with a large number of students, the number of students is increased to 50. From the comparison of Figure 3(c),(d), it can be found that peer learning with teacher guidance can make students with a team leader rotation mechanism better reach consensus.



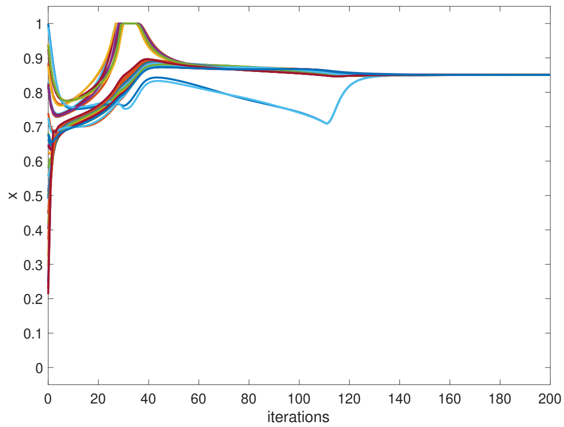
(a) $N = 20$, no teacher-guided fully connected network with team leader rotation mechanism



(b) $N = 20$, teacher-guided fully connected network with team leader rotation mechanism



(c) $N = 50$, no teacher-guided fully connected network with team leader rotation mechanism



(d) $N = 50$, teacher-guided fully connected network with team leader rotation mechanism

Figure 3. The convergence for CAISD.

6. Conclusions

This paper introduces an innovative approach to teacher-guided peer learning by using a continuous action iterated dilemma and a team leader rotation mechanism. In the previous results, the interactive relationship between students is required to be fixed, but it is difficult to achieve in the actual classroom. On the other hand, each student has his own unique personality. Therefore, this paper adopts some new ideas. First, a team leader rotation mechanism is proposed to make sure each student has the opportunity to become a team leader, which enhances students' sense of participation and improves classroom efficiency. Second, based on CAID, we design a model to describe students' behavior in complex environments. The advantage of the CAID model is that it uses multi-layer nonlinearity, which has higher accuracy in describing the behavior of students. In terms of application, we use the Lyapunov method to prove the stability to show that the model is reliable. It is worth noting that changes in the parameters do not affect the Lyapunov function, which reveals that the range of application of the model is wide. For example, teachers can implement a team leader rotation mechanism to encourage student participation and foster leadership skills. Additionally, the CAID model can be used to more accurately describe student behavior in complex learning environments, contributing to personalized education. However, the model does not account for the additional cost of teacher guidance. Under the rotation leadership mechanism, management and supervision may become more complex. Ensuring that everyone fulfills their leadership responsibilities may require extra effort, which is a further consideration for the ongoing development of this model.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The author declares there is no conflicts of interest.

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