

Retraction

Retracted: Application Research of Time Delay System Control in Mobile Sensor Networks Based on Deep Reinforcement Learning

Wireless Communications and Mobile Computing

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their

agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] W. Zhu, T. Garg, S. Raza, S. Lalar, D. D. Barak, and A. W. Rahmani, "Application Research of Time Delay System Control in Mobile Sensor Networks Based on Deep Reinforcement Learning," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 7844719, 7 pages, 2022.

Research Article

Application Research of Time Delay System Control in Mobile Sensor Networks Based on Deep Reinforcement Learning

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One of the main problems of networked control systems is that signal transmission delay is inevitable due to long distance transmission. This will affect the performance of the system, such as stability range, adjustment time, and rise time, and in serious cases, the system cannot maintain a stable state. In this regard, a definite method is adopted to realize the compensation of network control system. To improve the control ability of mobile sensor network time delay system, the control model of mobile sensor network time delay system based on reinforcement learning is proposed, and the control objective function of mobile sensor network time delay system is constructed by using high-order approximate differential equation, combined with maximum likelihood estimation method for parameter estimation of mobile sensor network time delay, the convergence of reinforcement learning methods for mobile sensor network control and adaptive scheduling, and sensor network time delay system control model of multidimensional measure information registration in strengthening tracking learning optimization mode to realize the adaptive control of mobile sensor network time delay system. The simulation results show that the proposed method has good adaptability, high accuracy of estimation of delay parameters, and strong robustness of the control process.

1. Introduction

Recent advances in wireless telecommunications and electronics have opened the way for the development of low-cost, low-power, and multifunctional sensor nodes that are small in size and wirelessly connect. Merely a little distance, the tiny sensor nodes, sensor components, data processing components, and connection components are supplied, allowing you to apply the sensor idea. Network sensor networks are an essential component of today's environment step up from standard sensors [1, 2]. Wireless sensor network (WSN) is a new mode of information acquisition and

processing which integrates sensor, embedded, wireless communication, distributed information processing, and other technologies. It is widely used in military, national security, environmental science, traffic management, disaster prediction, medical and health care, manufacturing, urban information construction, and other fields. In the Ministry of Industry and Information Technology released in November 2011, the Internet of Things "twelfth five-year" plan, the emphasis is put forward: in the field of wireless sensor networks, the need for sensor nodes and operating system, close range wireless communication protocol, sensor network networking technologies such as research,

developed low power consumption, high performance, and applicable range of the wireless sensor network systems and products. It shows that both at the national level and in the field of industrial application, wireless sensor network is believed to have a large application market and development potential in the future. Under the current wave of the industrial Internet, many traditional industrial production modes have carried out the corresponding technological innovation and upgrading, such as the optimization of the production process on the industrial site and the optimal allocation and coordination of social production resources. All above application scenarios require the wireless sensor networks to transmit real-time production data, supply, and demand information or equipment status back to the control center, to provide important reference data for production optimization and resource scheduling [3].

The wireless sensor network (WSN) is an infrastructure-free wireless network that analyzes system, physical, and environmental parameters through the ad hoc distribution of such a large number of wireless sensors. WSN controls and monitors the environment in a specified region by utilizing sensor nodes in combination with an embedded CPU. They are linked to the base station, which serves as the processing unit again for WSN system [4, 5]. With the development of mobile sensor network communication technology, mobile sensor network transmission is adopted to carry out large-scale data transmission and realize mobile sensor network data balanced scheduling and adaptive allocation; to improve the fidelity and transmission efficiency of data transmission, mobile sensor network time delay control is needed in the design of mobile sensor network. Combined with the design of mobile sensor network time delay control algorithm, the optimization design of mobile sensor is carried out; this paper studies the time-delay system control model of mobile sensor network and combines the channel equalization control method to improve the data and information transmission quality of mobile sensor network. The research on time-delay system control method of mobile sensor network has attracted great attention. However, the main shortcoming of the wireless sensor network of mobile sink node is that it increases the time delay of the network, and the data detected by the sensor node must be stored temporarily in the cache of the node and can only be forwarded to the mobile node when the mobile node moves nearby. This results in excessive delay, which in some cases cannot be tolerated. For example, in the case of pollution monitoring in cities, when there is an emergency sudden leakage of data, it must be transmitted to the base station for processing before causing serious consequences. Wireless sensor network has been widely used in industrial production, intelligent transportation, environmental monitoring, and other fields. The main challenges are focused on real-time, energy management, deployment and positioning, routing, data fusion and compression, etc. The purpose is to solve the problem of maximizing the utility of wireless sensor network under the limited energy.

In recent years, to solve the problem of unbalanced energy consumption of traditional wireless sensor network nodes, the network connectivity and coverage cannot be

guaranteed. Some researchers propose to introduce moving sink nodes to solve the problem, i.e., moving sink wireless sensor networks (MWSNs). Lin and Yan established a mathematical model of the operation process of ZigBee standard wireless network of the remote monitoring system based on Markov chain device. This model is used to evaluate the operation process of MAC CSMA/CA algorithm of IEEE802.15.4 ZigBee standard [6]. A new integral inequality is developed by using Wirtinger integral inequality and Leibniz-Newton formula [7]. The ZigBee protocol was designed to transport data in high-frequency RF situations such as those seen in commercial and industrial applications. The new version expands on the present ZigBee standard by unifying market-specific application profiles, allowing any device, independent of market designation or purpose, to be wirelessly joined in the same network. Furthermore, a ZigBee certification procedure ensures that devices from different manufacturers may communicate with one another [8]. Guo et al. adopt the method of delay partition, by constructing an augmented Lyapunov-Krasovskiy functional with three and four integrals and using some standard integral inequality techniques, obtained the asymptotic stability criterion of the relevant neural network. By converting the sampling period into a bounded time-varying delay, the error dynamics of the generalized neural network considered is derived using a dynamical system with sampling [9]. These and other sensor network applications necessitate the use of mobile intermittently connected methods. Many algorithms and algorithms for typical wireless ad hoc networks have been suggested, but they are not well adapted to the particular characteristics and application needs of sensing devices [10, 11]. Khujamatov et al. established a mathematical model of the operation process of ZigBee standard wireless network of a remote monitoring system based on Markov chain device. This model is used to evaluate the operation process of MAC CSMA/CA algorithm of IEEE802.15.4 ZigBee standard. The characteristic of this mathematical model is that it considers the load level of network elements and the potential malformation of transmission packets under the influence of interference. The developed mathematical model is used to analyze the main characteristics of the network operation process, such as the dependence of the successful transmission probability of packets on the system load (number of nodes and minimum length of competing windows) and the dependence of the bandwidth of channel noise on the system load (minimum length of competing window) [12]. Reinforcement learning is a subfield of machine learning. It all comes down to taking the appropriate actions to maximize your profit in a particular situation. A number of applications and computers utilize it to find the best possible action or course in a given event. Reinforcement learning differs from supervised learning in that the answer key is included in supervised learning, allowing the model to be trained with the correct answer, whereas reinforcement learning does not include an answer and instead relies on the reinforcement agent to decide what to do to complete the task. In the absence of a training dataset, it is compelled to learn from its own experience [13, 14]. Reinforcement learning is used

to solve node scheduling and routing problems in wireless sensor networks. Finally, simulation experiments are carried out to demonstrate the superiority of the proposed method in improving the control ability of mobile sensor network time delay system.

Sensor network has a large application market and development potential. This method can effectively control the mobile sensor network time delay system, and the output time delay is smaller, the stability is better, and the bit error rate is lower.

2. Transmission Delay Control and Parameter Analysis of Mobile Sensor Network

2.1. Composition of Routing Transmission Delay. There are two types of data operations in MWSNs: (A) The observer issues query instructions, and the query instructions go through the base station, mobile chat, cluster head, and finally to the sensor that detects the data; after receiving instructions, the sensor will implement data sampling. After the sampling, the data will be transmitted hop by hop to the sensor cluster head for storage, waiting for moving chat to collect data, and finally, the data will be returned to the base station to query the data, which is a passive network, as shown in Figure 1(a). There is no query instruction for data operation. The monitoring data will be sent out only when the monitoring data of a node exceeds its own monitoring threshold or is sampled according to a preset period (that is, it is based on events and time driven, respectively). Through the cluster head storage, moving sinks down to the base station, i.e., an active network, as shown in Figure 1(b).

In wireless sensor network measurement and control system, due to its own characteristics, when transmitting information, time delay with the packet loss phenomenon is inevitable, so in the greenhouse wireless sensor network measurement and control system also has this problem the topic. We assume that τ_1 for the underlying through gathering the information collected by the sensor node and then transmitted to the monitoring center through the base station by gathering node generated by the time delay, τ_2 after optimization algorithm to the control center, and control information via the base station transmitted to a base station will converge node; it generated when the control node transmission delay. Here, it is assumed that the monitoring center and control node are event driven; the sensor node is clock driven. Assume that the total extension of the closed loop is less than the sampling period T , and ignore the noise interference in the measurement and control system. When the packet loss occurs in the system, we make it resend. Therefore, for the system, the packet loss can be treated as a special delay.

Based on the active data operation mode, the transmission process of the sensor node sending data packets to the destination base station is divided into the following stages:

- (A) n_i Sensor nodes form a static cluster. Data collected by nodes in the cluster reaches the cluster head after multiple hops, and the delay is τ_{s0}

- (B) The sensor node or cluster head waits for the moving node M_k to enter its transmission range [3]. When M_k enters transmission range, the transmitter node (or cluster header) sends data to. The time delay is τ_{s0} , referred to as waiting time delay M_k
- (C) The data carried by M_k gradually approached to the target base station through several relays of moving sinks, and the time delay was measured as τ_{mm}
- (D) Mobile budget node transmits data to the base station nearest to itself. The time delay is τ_{mun}
- (E) Data is transmitted between base stations and finally arrives at the destination base station. The time delay is τ_{bb}
- (F) Thus, the time delay of a packet from being produced to being transmitted to the user can be calculated as D^{total}

$$D^{\text{total}} = \tau_{sc} + \tau_{sm} + \tau_{nm} + \tau_{mb} + \tau_{bb}b, \quad (1)$$

where τ_{sc} and τ_{sm} delay is the main components affecting network delay, compared with τ_{sc} , and τ_{mn} , τ_{mb} , and τ_{bb} stages have a very mature transmission technology (ad hoc mobile communication technology, etc.); they are predictable and do not vary much. In addition, in some application models, the mobile sink node is a user; that is, $D^{\text{total}} \approx \tau_{sc} + \tau_{sm}$. Therefore, this time delay study mainly analyzes these two parts.

2.2. Reinforcement Learning Model for Sensor Network Delay System Control. Reinforcement learning method is used to carry out convergence control and adaptive scheduling of mobile sensor network. M sink nodes are set to collect the transmission information of the mobile sensor network. The distribution amplitude of the network output bit sequence flow is AC, and the coherent distribution sources transmitted by the mobile sensor network are P interference signals; the discrete signal controlled by the mobile sensor network delay system is x . Let the code feature sequence of the original input mobile sensor network be $x = [x(0) \cdots x(n-1)]$, where $X(n)$ is the bit stream transmitted by the finite length discrete mobile sensor network, $0 < k < n-1$. The channel model of mobile sensor network delay system control obtained by vectorization processing method is as follows:

$$X(k) = \sum_{n=0}^{N-1} x(n) \exp\left(-j \frac{2\pi}{N} nk\right), \quad (2)$$

where $0 < k < n-1$ represents the length of data transmitted by the mobile sensor network, signal $X(n)$ is processed by the discrete orthogonal wavelet transform, and $X = \text{DEF}(x)$ represents the bandwidth controlled by the mobile sensor network delay system. In the discrete distribution sequence x , the enhanced tracking learning method is used to carry out channel equalization control of mobile

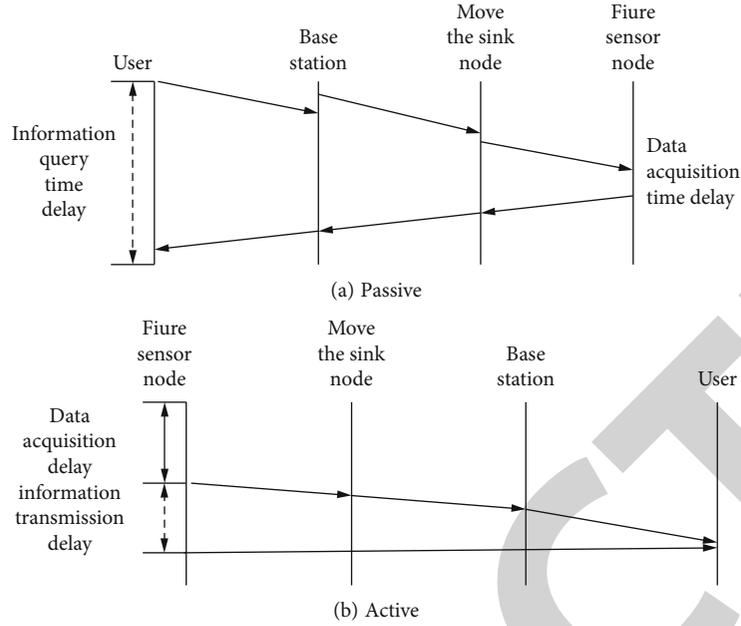


FIGURE 1: Schematic diagram of terminal-to-break network.

sensor network transmission [12]. By analyzing the computational complexity of each iteration, the characteristic quantity of statistical information of mobile sensor network time-delay system control is obtained as follows:

$$X = [X(0), \dots, X(N-1)]. \quad (3)$$

In the transmission channel of mobile sensor network, the relation point between vectorization and Kronecker product satisfies $j=0, 1, \dots, M$; the energy function controlled by the time delay system of mobile sensor network is $E_j = \sum_k |C_i(k)|^2$; for integer N_0 and N_1 transmission channels, the pass band of mobile sensor network transmission delay system control is $C^{(j)}$, and reinforcement learning method is used to carry out mobile sensor network channel equalization control. Each block signal corresponds to the characteristic number of Baud interval sampling at 1-dimensional distance. The scattering point function of time delay control at each distance is as follows:

$$\begin{aligned} C^{(0)} &\leftarrow \text{DFT}\{x\}, \\ \{C^{(j)}, W^{(j)}\} &\leftarrow \text{AFB}(C^{(j-1)}, N^{(j)}, N_1^{(j)}), \\ w^{(j)} &\leftarrow \text{DEF}^{-1}\{W^{(j)}\}, \\ c^{(j)} &\leftarrow \text{DEF}^{-1}\{C^{(j)}\}, \end{aligned} \quad (4)$$

where N represents the length of data transmitted by the mobile sensor network and J is the frequency of characteristic sampling. Based on the above analysis, a reinforcement learning model of sensor network time-delay system control is built, and the mathematical modeling of system control is

carried out in combination with the time delay estimation method.

Applications are being developed in a range of scientific fields. Extensive seismic testing, habitat monitoring, and intelligent transportation systems are just a few of the exciting ongoing endeavors [15, 16]. Home and building automations, as well as military applications, are important application fields. The performance gain of mobility on the network is verified by simulation. To simplify the simulation, the data collection method uses mobile sink nodes to collect data directly from each sensor node. After sensing and collecting data, the sensor node will cache the data in memory and wait for the mobile sink node to collect. The physical layer adopts ZigBee wireless network technology, and the MAC layer and routing layer protocols of sensor nodes, respectively, use S-MAC protocol [17] and TTOD protocol [18]. ZigBee is a set of greater communication systems great for small projects that require wireless connectivity. It is used to create connectivity using small, minimal digital radios, such as for home automation, medical device data gathering, or other reduced, reduced demands. As a result, ZigBee is a reduced, reduced wireless ad hoc network that works near to each other. The ZigBee standard outlines a technology that is intended to be simpler and less expensive than existing wireless personal area networks (WPANs) such as Bluetooth or wider wireless networking such as Wi-Fi. Examples of applications include wireless switches, home energy monitors, traffic management systems, and other consumer and industrial equipment that require short-range low-rate wireless data transfer [19, 20]. 1000 static sensor nodes are uniformly deployed in a 10000 m \times 10000 m area, and the moving chat moves in the moving model's random direction. The packet generation rate of the sensor node is 1 packet/cycle, and the simulation runs for 1 cycle. Default parameters are used for other parameters [21].

Performance indexes such as average data transmission delay, data transmission success rate, and packet sharing rate are mainly investigated [22]. The average data transmission delay is defined as the time experienced by data from generation to successful receipt of the moved chat nodes, which is mainly the waiting time. To compare the relationship among speed v , number m , transmission radius r , and packet size L of moving sinks, as shown in Figure 2, the more m move sinks, the smaller the time delay. The simulation results are in good agreement with the above analysis. The results also show that the appropriate moving sink velocity should be selected. When the velocity v of moving sink is too low, the sensor node needs to wait a long time to get the data transmission service of moving sink. And if the speed v of moving chat is too fast, although the probability of meeting the chat node and sensor node is increased, it leads to long sinks which cannot be transmitted within a service period (in real network, the packet can only be transmitted in fragments).

3. Experimental Test Analyses

The delay compensation is realized by designing the predictive controller, and the stability condition of the system and the expression of the controller are obtained by choosing the Lyapunov function reasonably. Considering the case of packet loss, the delay compensation is still compensated by predictive controller, and the packet loss problem can be established as a random Bernoulli sequence, so the model established for the network control system becomes a stochastic control system model. After that, the stability of the established stochastic system is studied, and the controller is solved.

To test the method in the implementation of mobile sensor network time delay system control performance, the analysis of time delay, mobile sensor network time delay system control node distribution in homogeneous array area of 200 m by 200 m, mobile sensor network with element transfer rate of 20 k Baud, time delay control system of carrier frequency for 24 kHz, the output signal-to-noise ratio of -15 dB, initial coverage radius for the sensor network is taken of 10 m, and the node energy $E_0 = 200$. Firstly, packet loss is established as a random Bernoulli sequence with values of 0 and 1, and the stability of the stochastic system is given. By adopting predictive control scheme to deal with delay, the influence of delay and packet loss on NCS is improved effectively. Then, the delay compensator designed at the actuator end is used to select the latest control data to compensate the delay from the controller to the actuator. According to the above simulation environment and parameter settings, the mobile sensor network time delay system is controlled, and the distribution of the output transmission code sequence of the mobile sensor network is obtained, as shown in Figure 2.

Taking the data in Figure 2 as the research object, the mobile sensor network time delay system is controlled, and the optimized control output is shown in Figure 3.

Analysis diagram 3, using the method can effectively control the mobile sensor network time delay system, the

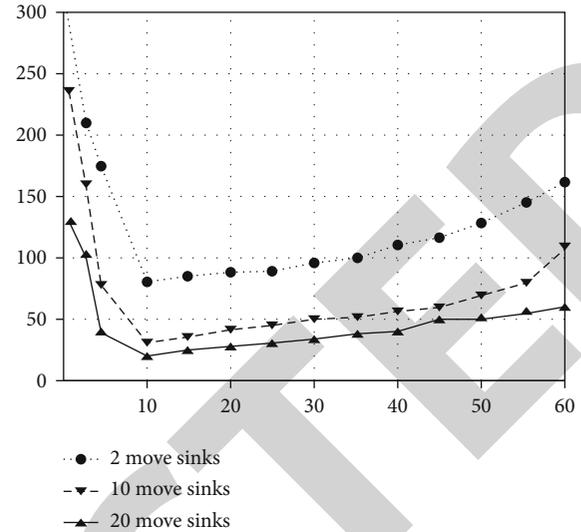


FIGURE 2: Output code sequence of mobile sensor network.

output of the time delay is small, stable, improve the transmission stability of the mobile sensor network, test the output error, by contrast, the results are shown in Table 1, as shown in the analysis, the method to control after the mobile sensor network time delay system reduces the output bit error rate of the network [23].

Mobile sensor network time delay control is combined with the design of mobile sensor network time delay control algorithm and mobile sensor optimization design [24]. The extraction of mobile sensor network, transmission delay information of the average mutual information, combined with squares estimation method and maximum likelihood estimation method, control the time delay and parameter estimation, in strengthening tracking learning optimization mode adaptive control to realise the mobile sensor network time delay system, is based on the reinforcement learning system control model of mobile sensor network time delay. It improves the transmission balance of mobile sensor network and reduce the delay [25]. The results show that the proposed method can effectively control the time delay system of mobile sensor network, and the output time delay is smaller, the stability is better, and the bit error rate is lower.

4. Analysis

In recent decades, more and more experts and scholars have paid attention to the research and application of time-delay systems. The phenomenon of time delay often affects the parameter performance of the system and sometimes even makes the system collapse. Therefore, the theoretical study of time delay system has important theoretical significance and practical value. For a system with time delay, the first thing to consider is its stability. Under the premise of stability, the maximum time delay allowed by the system is often the focus of research. Many experts and scholars put forward a series of innovative ideas and formed a relatively perfect theoretical system. For the study of time-delay systems, many theoretical achievements have been made, such as

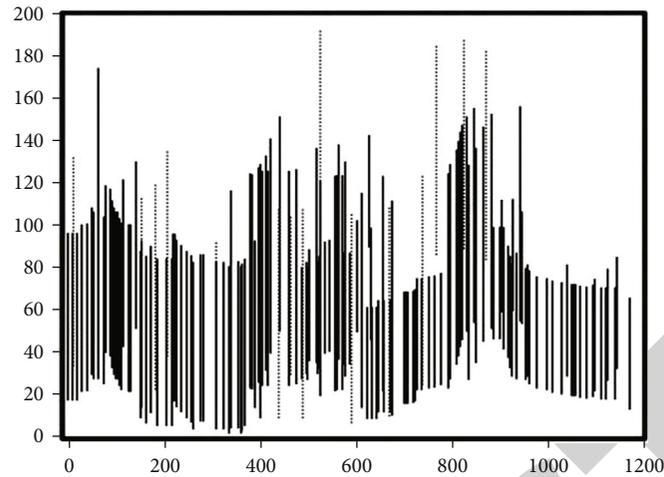


FIGURE 3: Optimized control output of mobile sensor network delay system.

TABLE 1: Comparison of output bit error rates.

Signal to noise ratio/dB	Methods/dB	The literature/dB [12]	The literature/dB [9]
-10	0.063	0.143	0.254
-8	0.041	0.121	0.143
-6	0.023	0.112	0.146
-4	0	0.103	0.122
0	0	0.072	0.110

time-delay of variable time-delay system research, guaranteed performance control of variable delay systems, and other related robust stability.

5. Conclusions

The method in this paper reduces the output bit error rate of the network after controlling the delay system of the mobile sensor network. The bit error rate is reduced to about 0. A new adaptive recursive channel estimation algorithm, in which the last channel estimation, is used to initialize the iteration process of the current channel estimation; thus, the channel estimation and tracking are performed. In addition, the channel estimation is recursively updated, and the matrix inversion method is applied to reduce the complexity of calculation [19]. According to the analysis and simulation of the new algorithm, compared with the RLS algorithm, the proposed algorithm can estimate and track the channel changes more accurately in the fast fading environment without affecting the performance of the system error, which shows that the proposed algorithm is robust to the high Doppler shift. Mobile sensor network time delay control is combined with the design of mobile sensor network time delay control algorithm and mobile sensor optimization design. Time delay control of mobile sensor network time delay system based on reinforcement learning control mathematical modelling Wen-wen Yang, the extraction of mobile sensor network, transmission delay information of the average mutual information, combined with squares estimation

method and maximum likelihood estimation method, time delay control of mobile sensor network time delay system based on reinforcement learning control mathematical modelling Wen-wen Yang, and the parameter estimation. The adaptive control of mobile transmitter network delay system is realized in the enhanced tracking learning optimization mode, which improves the transmission balance of mobile sensor network and reduces the delay. This method can effectively control the time delay system of mobile sensor network, and the output time delay is smaller, the stability is better, and the bit error rate is lower.

Data Availability

All the data pertaining to this article is in the article itself.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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