Research Article

Research on Evaluation Method of Sports Events Based on Edge Algorithm

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In view of the high computational cost and long computational time of IoT edge algorithm in traditional sports event evaluation, this paper optimizes IoT edge algorithm by introducing deep reinforcement learning technology. Set the IoT edge algorithm cycle through the IoT topology to obtain the data upload speed. In order to improve the evaluation efficiency of sports events, the process of edge algorithm is designed. The contribution rate of evaluation index is calculated, and the consistency, minimum deviation, and minimum difference of the results are taken as the standard to design the evaluation method of sports events. In order to verify the performance of the optimized edge algorithm, the test dataset and test platform are set up and the comparative experiment is designed. Compared with the traditional methods, the edge algorithm based on DSL has lower computational cost, shorter computational time, higher evaluation accuracy, and more practical results.

1. Introduction

As one of the important parts of the social subsystem, physical education has penetrated into every aspect of the society. With the rebirth of modern Olympic Movement and the formation of Olympic economy, sports events have a close relationship with other social factors such as economy, politics, and culture and play an active role in the modernization of cities. Since the middle of last century, the main reason why major cities in the world bid for sports events is that the city authorities have seen that holding sports events can temper and enhance the administrative governance ability of the host city government or the host country government, thus being conducive to enhancing the status and reputation of the host city and expanding the popularity of the city. For example, the city of Atlanta is known as a world sports center city for its advanced sports facilities, and Shanghai is accelerating the pace of building a first-class sports center city in Asia [1]. Besides promoting the political influence of the city, the holding of sports events also brings great economic effects to the host city and establishes a good self-renewal mechanism and perfect internal coordination mechanism. Sports events on the host city’s economic pull, mainly reflected in the stimulation of investment, expanding consumption, increasing employment and optimizing economic structure. In particular, the tertiary industry in the tourism, catering industry, social services, media and communication industries, etc., the tertiary industry in marketing methods, service technology, business philosophy, and other aspects are gradually in line with the international standards [2, 3].

In order to evaluate sports events effectively, some good research results have appeared at present. Literature [4] proposed a modeling method for intelligent evaluation of sports events. Firstly, the network architecture of sports events is understood from three aspects of wireless transmission, access and network technology, and the feasibility of the application of the above technologies in sports events is illustrated through the analysis of coverage, capacity, delay and rate, and other indicators. Secondly, it clarifies the principles that the evaluation model should follow. Finally, the fuzzy comprehensive evaluation mechanism is used for
fuzzy matching, the weight distribution set is established, the fuzzy evaluation results are obtained, and the normalization process is done to construct the final evaluation model. However, the index system of this method has many variables, and the evaluation process is complex. It does not follow the principle of conciseness and application, and has the problems of low identification accuracy and poor evaluation efficiency. Literature [5] proposed a comprehensive evaluation method of sports events based on cosine similarity. The above method calculates the cosine similarity between the evaluation index vector of each network node of sports events and the index vector of the ideal node, obtains the comprehensive ranking result of nodes, and finally selects the best nodes to complete the comprehensive evaluation of sports events. However, this method has a weak ability to resist the attack of the method nodes of sports events under the information condition.

Therefore, how to evaluate the sports events scientifically, comprehensively, and reasonably, especially the economic and social effects, has become the focus of attention. The evaluation of sports events mainly includes the economic and social aspects. Through the specific analysis of the evaluation content and the weight calculation of the evaluation index, the whole evaluation of sports events is optimized, and the reference experience is provided for the organization and evaluation of sports events in the future.

The research contributions of this article include the following:

1. In view of the high computational cost and long computational time of IoT edge algorithm in traditional sports event evaluation, this paper optimizes IoT edge algorithm by introducing deep reinforcement learning technology.

2. In order to improve the evaluation efficiency of sports events, the process of edge algorithm is designed. The contribution rate of evaluation index is calculated, and the consistency, minimum deviation, and minimum difference of the results are taken as the standard to design the evaluation method of sports events.

3. Compared with the traditional methods, the edge algorithm based on DSLL has lower computational cost, shorter computational time, higher evaluation accuracy, and more practical results.

The remainder of this paper is organized as follows. Section 2 introduces the principles and indicators for evaluation of sports events. Section 3 discusses the sports event evaluation method based on edge algorithm. Section 4 discusses experiment and analysis. Section 5 presents the conclusions of the study.

2. Principles and Indicators for Evaluation of Sports Events

2.1. Evaluation Principles of Sports Events

2.1.1. Principle of Objectivity. Objectivity means that the evaluation of sports events follows objective laws, seeks truth from facts, and cannot be subjective and arbitrary. The principle of objectivity should be adhered to. First, evaluators should avoid various preconceived concepts and overcome subjective randomness and one-sidedness. Secondly, evaluators should conduct in-depth investigation to comprehensively and systematically master reliable information [6]. Thorough investigation and research and comprehensive and systematic grasp of information are the basic requirements for adhering to the principle of objectivity and the basic guarantee for scientific evaluation of sports events.

2.1.2. Principle of Benefit. The principle of benefit is that the evaluation of sports events should be based on the results and returns of investment as the standard to identify its merits. In carrying out the principle of benefit, we should deal with the relationship between the financial benefit and national economic benefit. The interests of different subjects are also different. Investment enterprises and lending banks pay more attention to financial benefits, while countries and regions pay more attention to national economic benefits [7]. Therefore, it is necessary to make different decisions. For a sports event, we can judge its success from three points: one is good financial benefit, and the other is general financial benefit, and the other is outstanding national economic benefit. We also believe that the event is successful from regional economic considerations.

2.1.3. Principle of Standardization. The principle of standardization is that the qualitative and quantitative analysis methods adopted in the evaluation work must conform to the state provisions and be scientific. The standardized system of evaluation of sports events constitutes the stable structure and basic content of the evaluation subject. In general, the use of a standardized approach does not affect the creative work of evaluators, but is a necessary condition for their creative work to be easily recognized [8].

2.1.4. Principle of Dynamic Order. Sports events are a complex group of events, especially the top events such as the Olympic Games, from the beginning of the project to the successful conclusion of the Olympic Games, the long cycle, involving a wide range is unparalleled. Therefore, the overall project should be completed in a more sequential and
phased manner, with relevant evaluations carried out at each implementation stage and organized at each stage of the evaluation [9].

2.2. Sports Event Evaluation Process. For the sports events, they are divided into the preparation stage, the operation stage, and the posteffect stage of the sports events. The corresponding evaluations are the precompetition evaluation, the follow-up evaluation, and the postcompetition evaluation. This article mainly studies the impact of sports events on the socioeconomic aspects for analysis. One of the main objectives of sporting events is to obtain some economic benefits [10, 11]. Therefore, the economic evaluation of sports events is an important part of the evaluation of sports events. The economic evaluation of sports events is the same as the economic evaluation of other items. The scope of financial evaluation of sports events is from the perspective of the host unit, in accordance with the current financial and taxation system, the financial evaluation of sports events mainly from the cost and income of a comprehensive evaluation and analysis. But the sports event’s national economy appraisal embarks from the national and the social angle, analyzes and calculates the sports event to the society and the national economy contribution. Therefore, sports events need the guarantee of security and communication networks.

In the process of comprehensive evaluation of sports events, the methods of combination of qualitative and quantitative, or the analytic hierarchy process, etc. are adopted for comprehensive evaluation. No matter which method or means is adopted, attention should be paid to the effectiveness and reliability of evaluation, because the ultimate purpose of comprehensive evaluation is to give an evaluation of whether the decision is feasible and whether the success or failure of sports events is good or bad [12]. From the above main procedures, the evaluation procedures of sports events can be obtained as shown in Figure 1 below.

3. Sports Event Evaluation Method Based on Edge Algorithm

3.1. Deep Reinforcement Learning Optimization Edge Algorithm

3.1.1. Cycle Setting of IoT Edge Algorithm. For the purpose of this research, it is necessary to analyze the topology of Internet of Things and set the cycle of edge algorithm according to the analysis results. Generally, the topological structure of Internet of things can be divided into plane structure and hierarchical structure. According to the related characteristics of Internet of things, the hierarchical results are used as the research object in this study, and the focus is on its network model. The difference between hierarchical topology and planar topology is that this structure is more hierarchical, can complete the end-to-end communication between multiple subnetworks, and uses one of the nodes as a route to achieve the transmission of data information [13].

The Internet of Things consists of primary users, auxiliary users, and local base stations. Set the working index set in the network as \( K = \{0, 1, \ldots, n\} \), where \( K = 0 \) is set as index 1, 1, 2, \ldots, \( K \) is set as index 2. If index no. 1 is set to complete intensive computing tasks within the specified time, the remaining part of index no. 2 should be cleared in the network and the calculation results should be returned in time. According to the randomness of the business data of the Internet of Things and renewable energy, the interval time of continuous time scale division is set as \( \Delta t \). The decision moment and decision cycle \( \Delta t \) can be dynamically adjusted by using the above cycle to meet the complexity and variability of the edge algorithm of the Internet of Things [14]. At each calculation decision moment point, the generation rate and output rate of business data are set as \( W \) and \( E \), respectively; then, the accumulated data volume and energy value of the Internet of Things in the calculation cycle of constant time interval can be expressed in the following formulas:

\[
W = P(t) \cdot \Delta t, \quad (1)
\]

\[
E = \alpha(t) \cdot \Delta t. \quad (2)
\]

In the above formula, \( P(t) \) is the data receiving function of the Internet of Things, and \( \alpha(t) \) is the energy exchange function. The above formula is used to control the data
generated in the cycle of the edge algorithm [15]. In the case of different calculation cycles, in order to facilitate the development of calculation, the business data generation rate and energy attainment rate are both represented in the form of independent identical distribution. Set the bandwidth of the wireless broadband in the Internet of Things as $M$, and there is only one base station in the Internet of Things, ignoring the interference of the base station, the data uploading rate of the Internet of Things can be expressed as

$$r = M \cdot \frac{\alpha(t) \cdot f_i}{p(t) \cdot \chi^2}$$ (3)$$

In the above formula, $f_i$ represents the data transmission power of users in the Internet of Things, and $\chi^2$ is set as the variance value of Gaussian white noise. The above part is used to complete the design of the IoT edge algorithm cycle, and the results are used as the data basis for constructing the edge algorithm execution process.

3.1.2. Set the Execution Process of the Edge Algorithm. The above analysis results are used as the basis for the construction of the execution process of the edge algorithm of the Internet of Things, and the deep reinforcement learning technology is used to complete the execution process of the edge algorithm.

For the local computing part $\lambda_i$ of the Internet of Things, $y$ is defined as the delay of local execution, which includes the processing time of the server, and $u_i$ is set as the CPU frequency during calculation. Then, the execution delay $y$ can be expressed by the formula:

$$y = \frac{\lambda_i \cdot u_i}{d_i}.$$ (4)

In the above formula, $d_i$ is the length of communication channel. Set $c_i$ to be the power consumption generated when executing locally. In the ideal state, the energy consumption of local execution is 0. Therefore, according to formula (4), the general situation of execution delay can be expressed as

$$y' = \frac{\lambda_i \cdot u_i}{d_i}.$$ (5)

According to the above formula, the execution process of edge algorithm is controlled. Ensure that the energy consumption of the edge algorithm conforms to the characteristics of the Internet of Things. According to the data transmission speed calculated in formula (3), the delay time of the calculation process can be expanded and calculated, and then,

$$t_1^0 = \frac{y' \cdot r}{R}$$ (6)

The time expansion control in the execution process of the edge algorithm of the above formula is adopted. According to the execution process of the edge algorithm designed in this part, in-depth reinforcement learning technology is integrated into the resource allocation of the edge algorithm for sports event evaluation.

3.1.3. Evaluation Efficiency Optimization of Sports Events Based on Edge Algorithm. In this part, the CNN model in deep reinforcement learning technology is used as the design basis to realize the resource allocation of the evaluation of sports events based on the edge algorithm of the Internet of Things. In this part, convolution processing is mainly used to complete the reasonable allocation of resources [16, 17].

According to the relevant knowledge of signals and networks, the convolution operation of two signals in the decision time cycle can be expressed as follows in the form of formula:

$$R = g(t) \cdot h(t).$$ (7)

In the above formula, $g(t)$ and $h(t)$, respectively, represent the signals in the edge algorithm. Through the translation and multiplication of the two signals in the time period, the discrete sequence $l(n)$ and $j(n)$ in the resource allocation of sports event evaluation can be obtained. The convolution result is reflected in the discrete form, and then,

$$R(n) = j(n) \cdot l(n).$$ (8)

Using the above formula, set the number of connections in the IoT edge algorithm. According to the parameter characteristics of the CNN model, the weights and biases in the allocation process are set as the connection number, and the number of parameters in the IoT edge algorithm can be expressed as

$$N = (m_c \cdot s_k \cdot q_k + 1).$$ (9)

In the above formula, $m_c$ is the number of channels in the calculation, and $s_k$ and $q_k$ are the width and height of the convolution kernel, respectively. The calculation amount of the calculation process can be obtained through this formula as follows:

$$Q = m_c \cdot s_k \cdot q_k.$$ (10)

Then, the reasonable distribution of the calculation amount can be expressed as

$$l(t) = \frac{m_c \cdot s_k \cdot q_k}{R}.$$ (11)

The above formula is used to complete the allocation of evaluation resources of edge algorithm for sports events. This part is connected with the design part above in an orderly way to realize the application of deep reinforcement learning in the edge algorithm of the Internet of Things. So far, the IoT edge algorithm method based on deep reinforcement learning has been designed.

3.2. Design of Evaluation Methods for Sports Events

3.2.1. Calculation of Index Contribution Rate. For complex evaluation objects, not all indexes have the significance of participating in evaluation. According to information theory, the role of each indicator in the evaluation system depends on the amount of decision information it has. The larger the amount of information, the higher the role of
target evaluation, and the amount of information can be calculated by edge algorithm [18, 19].

The edge algorithm evaluates the importance of the index by combining the amount of information of all indexes, that is, the entropy weight. Assume that the initial index attribute matrix is expressed as $(c_i)_{mn}$ and $c_ij$ is the attribute value of the $i$ scheme under the $j$ index. Therefore, the contribution degree $c_ij$ of the $i$ scheme to the $j$ index attribute is expressed as

$$p_{ij} = \frac{c_ij}{\sum c_ij, j \in (1,m)}, \quad i = 1, 2, 3. \quad (12)$$

The contribution rate includes information that describes the sum of the three methods’ contribution rates to index $j$ in terms of entropy $T_j$.

$$T_j = -\sum_{i=1}^{m} p_{ij}, \quad i = 1, 2, 3. \quad (13)$$

If the index belongs to the interval type, the contribution rate and entropy of the upper and lower intervals of the index in all schemes are obtained, respectively, and the value in the interval entropy is taken as the total contribution rate of the index.

### 3.2.2. Evaluation Model Criteria Are Determined.

Before constructing the evaluation model, we must determine the standard of model construction, which also indicates the performance of the model. For the evaluation model in this paper, three criteria need to be analyzed: consistency of results, minimum deviation, and minimum difference [20]:

1. **Consistency of Results.** The criterion is that the evaluation results should not appear contradictory phenomena. In general, when the evaluation model has a unique solution, the model will automatically meet the result consistency criteria.

When the evaluation model has only one real solution, it is assumed that the solution is $(\mu_1, \mu_2, \ldots, \mu_m)$, and $\mu_j$ represents the comprehensive score of the target to be evaluated. Since $\mu_j$ is a real number, according to the partial order property of the set of real numbers, we can know that if $\mu_1 > \mu_2, \mu_2 > \mu_3$, then $\mu_1 > \mu_3$ must be obtained. Therefore, the final result for this group of solutions must meet the consistency requirements.

2. **Minimum Deviation.** The results obtained by this standard for the model should minimize the error of the target score to be evaluated and the result error of all known evaluators. There are multiple explanations for the types of deviation penalty functions, which can be expressed either as absolute value function, quadratic function, or in other forms. Taking the absolute value function and quadratic function as examples, this paper analyzes the minimum deviation expressions under these two definitions, respectively:

$$p_1 = \min \sum_{i=1}^{n} \sum_{j=1}^{m} |w_{jj} - c_{jj}'|, \quad (14)$$

$$p_2 = \min \sum_{i=1}^{n} \sum_{j=1}^{m} |w_{jj} - c_{jj}'|. \quad (15)$$

Minimum deviation is achieved on the principle of pairwise comparison. The differences between the two objectives are analyzed, and the differences between the two objectives are minimized.

3. **Minimum Difference.** This property indicates that the obtained result is as close as possible to the initial evaluation value, which is different from the minimum deviation. It is also expressed in the form of an absolute value function and a quadratic function:

$$p_1' = \min \sum_{i=1}^{n} \sum_{j=1}^{m} (\mu_j - d_{ij}), \quad (16)$$

$$p_2' = \min \sum_{i=1}^{n} \sum_{j=1}^{m} (\mu_j - d_{ij}), \quad (17)$$

where $\mu_j - d_{ij}$ represents the error between the score of objective $j$ in the evaluation result and the score of evaluator $i$.

Combined with the known properties of the evaluation model, the following evaluation model is constructed to meet the above requirements:

$$j = \min \sum_{i=1}^{n} \sum_{j=1}^{m} |c_{ij}'|, \quad (16)$$

$$G = \min \sum_{i=1}^{n} \sum_{j=1}^{m} |\mu_j - d_{ij}|, \quad (17)$$

s.t., $w_{jj} = \mu_j - \mu_j'$,

where $d_{ij}$ represents the known evaluation score and $\mu_j$ and $c_{ij}'$ represent the unknown quantity.

In order to facilitate the calculation of the above models, the combination of the above models can be simplified and the final evaluation model expression can be obtained as follows:

$$Z = T_j \sum_{j=1}^{m} \sum_{i=1}^{n} j + \sum_{j=1}^{m} \sum_{i=1}^{n} G. \quad (17)$$

### 4. Analysis of Experimental Test Results

In the process of this use, Python3.5 was used to realize the calculation process of this test. In order to make the test results more convincing, Google Cluster was used as the data set of this test, and CPU request, memory request, and other attributes were used to build test task samples. In order to ensure the effectiveness of the control of the test equipment, the server performance parameters are shown in Table 1.
The above setting part is used as the preparation stage of this test. The above setting results are used to complete the test process, and the differences between the calculation method after the intensification learning method and the method before the use of other technologies and without this technology are compared.

4.1. Server Time. In order to verify the server occupancy time of different methods in the Internet of Things edge algorithm, the server occupancy time of the proposed method, the method in [4], and the method in [5] were compared, and the results are shown in Figure 2.

As shown in Figure 2, the edge server occupancy times vary by method. For Figure 2(a), in the overall working environment, when the number of tasks is 200, the time of unoptimized edge servers is 73 s, the time of edge servers for the Edge Cloud IoT optimization method is 52 s, the time of improved cat swarm IoT optimization method edge servers is 48 s, and the time of servers for the Deep Reinforcement Learning optimization method is 8 s. Although the three methods can effectively reduce the server time, the time of this method is much lower than other methods, and the overall analysis of the above figure can get this conclusion.

For Figure 2(b), in some working environments, when the number of tasks is 500, the unoptimized edge server time is 42 s, the edge server time for the edge cloud IoT optimization method is 17 s, the improved cat swarm algorithm IoT optimization method edge server time is 22 s, and the server time for the deep reinforcement learning optimization method is 32 s. When the number of tasks is 800, the time taken by edge servers that have not been optimized is 58 s, the time taken by edge servers of the edge cloud cooperative optimization method of the Internet of Things is 21 s, the time taken by edge servers of the improved cat swarm algorithm optimization method of the Internet of Things is 31 s, and the time taken by servers of the deep reinforcement learning optimization method is 5 s. In some working environment, the server time of this method is obviously lower than that of other methods, which shows that this method has higher computational efficiency and strong applicability.

With the increasing number of tasks, in two different working states of edge servers, the algorithm using deep reinforcement learning technology can ensure the normal operation of the server. The use of deep reinforcement learning technology can effectively control the server time.

4.2. Server Power Consumption. On the basis of the above, the server power consumption of the above three methods is obtained through statistics, and the results are shown in Table 2.

Analysis of Table 2 shows that the server energy costs vary for different approaches. When the server running time is 10 hours, the energy cost of traditional method is more than 480 W, and the energy cost of proposed method is only 55 W. By analogy, the energy cost of this method is obviously lower than that of the other two methods. Deep reinforcement learning can be used to control the energy cost of edge server effectively.

4.3. Calculated Wait Time. In order to further verify the computational efficiency of different methods, experiments on average calculated waiting time under different tasks were added, and the results are shown in Figure 3.

Analysis of Figure 3 shows the number of different tasks and the calculation of different wait times. When the number of tasks is 100, the average computation waiting time of the deep reinforcement learning method is 8 ms, the average computation waiting time of the improved cat swarm algorithm is 58 ms, and the average computation waiting time of the edge-cloud cooperative method is 66 ms. When the number of tasks is 800, the average computation waiting time of the deep reinforcement learning method is 32 ms, the average computation waiting time of the improved cat swarm algorithm is 182 ms, and the average computation waiting time of the edge-cloud cooperative method is 166 ms. The method of this paper can improve the evaluation resource allocation ability of IoT edge algorithm, ensure the uniform calculation process, and improve the efficiency of IoT edge algorithm.

Combining the test results of the average computational waiting time, the test results of the energy cost of the edge server, and the test results of the occupancy time of the edge server, the edge algorithm based on deep reinforcement learning designed in this paper can effectively control the computational cost and complete the efficient edge algorithm process.

4.4. Comparison of Weight Accuracy Calculation Results of Different Methods. The calculation results of weight accuracy constructed by the method in this paper and the traditional method are shown in Figure 4.
The proposed method
Methods in [4]
Methods in [5]
Methods in [21]
Not optimized
Methods in [22]

(a)

(b)

Figure 2: Edge server elapsed time. (a) Application effect in all working environments. (b) Part of the application effect under the working environment.

Table 2: Server power consumption of different methods.

| Elapsed time (h) | The proposed method | Methods in literature [4] | Methods in literature [5] | Methods in literature [21] | Methods in literature [22] |
|------------------|----------------------|---------------------------|---------------------------|---------------------------|---------------------------|
| 10               | 55                   | 486                       | 495                       | 320                       | 176                       |
| 20               | 111                  | 887                       | 752                       | 589                       | 352                       |
| 30               | 120                  | 1154                      | 1124                      | 712                       | 470                       |
| 40               | 227                  | 1683                      | 1147                      | 934                       | 853                       |
| 50               | 414                  | 2018                      | 1955                      | 1406                      | 976                       |
| 60               | 457                  | 2559                      | 2458                      | 1769                      | 1253                      |

Figure 3: Average calculated waiting time under different methods.
By comparing the results, it can be seen that the model constructed by using the method in this paper is more consistent with the actual value, which effectively improves the inaccurate evaluation results caused by the relationship between indicators. The model based on edge algorithm can accurately mine the correlation between indicators and reflect the performance of the target to be evaluated. In addition, the evaluation time of the two methods is recorded, respectively, in the evaluation process. The results show that the proposed method consumes less time, improves the evaluation efficiency, and has scientific and practical value.

5. Conclusion

Deep reinforcement learning technology is introduced into the edge algorithm of Internet of Things. Convolution calculation is realized by CNN model to improve the efficiency of sports event evaluation. The following conclusions were drawn from the experiment:

1. Deep reinforcement learning technology can effectively reduce the server occupation time. In the whole working environment, when the number of tasks is 200, the server time of the deep reinforcement learning optimization method is only 8 s. In part of the working environment, when the number of tasks is 800, the edge server time of the deep reinforcement learning optimization method is 21 s.

2. Applying the deep reinforcement learning technology to the calculation method can effectively control the energy cost of the edge server in the calculation process. When the server running time is 48 hours, the energy cost of the deep reinforcement learning optimization method is only 246 W.

3. The method in this paper can improve the evaluation resource allocation capacity of the IoT edge algorithm, ensure the uniform calculation process, and improve the efficiency of the IoT edge algorithm. When the number of tasks is 800, the average waiting time of the deep reinforcement learning method is 32 ms.

In the future research, further optimization will be carried out on how to complete the edge algorithm more effectively, ensure the reliability and timeliness of task processing, and balance the load of all edge servers in the peak period.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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