A Next-Generation Computing Engine for an Embedded IoT Systems-Based Intelligent English Classroom Learning System

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Abstract. In order to improve the effect of intelligent English teaching, this paper explores the scientific connotation of the current intelligent classroom and the construction ideas of information technology courses based on the intelligent classroom supported by electronic schoolbag equipment. Moreover, algorithm analysis is performed on the next-generation computing engine of the Internet of Things platform. Based on the characteristics of a large number of intelligent heterogeneous network elements in the perception layer of the Internet of Things and the need for real-time processing of the perception data of the Internet of Things front-end, a ubiquitous storage model of the Internet of Things and a layered expansion ubiquitous storage strategy are proposed. Moreover, through in-depth research on the requirements and query technology of multi-objective decision-making applications in the Internet of Things, this paper proposes an efficient query method for multi-dimensional perception data. In addition, this paper constructs an English classroom learning system and conducts systematic evaluation through experimental teaching. The research results show that the teaching system constructed in this paper is effective.

Keywords: Smart English class; Internet of Things; computing engine; smart teaching; Revolutionizing Digital Art
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1 INTRODUCTION

Smart classroom is to build a classroom that can realize intelligent education and cultivate intelligent talents by fusing technology and teaching, and the teaching is easy, happy, high-quality and efficient, rather than a knowledge-based classroom. It can also be considered that the smart classroom is the use of a new generation of information technology in classroom teaching to achieve an efficient and intelligent classroom in the whole process of teaching before, during and after class, and it is a new stage in the development of classroom use of information technology [1]. In addition, smart classrooms can be understood from two levels of technology and teaching. From a technical perspective, a smart classroom is an open and intelligent teaching environment based on information technology such as big data, virtual simulation, electronic schoolbags, and smart mobile terminals. From the perspective of teaching, smart classroom is to use information technology to train students to "turn knowledge into wisdom", and it is a classroom that promotes the generation of students' wisdom [2]. However, no matter from which level it is understood, the smart classroom is a new type of classroom based on traditional classrooms that applies information technology to transform the teaching environment, change teaching methods, improve teaching effects, and cultivate students' ability for better development [3].

Although the development of education informatization in our country has made great progress, from the perspective of national conditions, our education form still stays in the industrial era of teaching organization based on the class teaching system, and the teaching methods basically use teacher lectures and demonstrations. Traditional method. Most of the students' learning methods are based on accepting learning. Such teaching methods have largely inhibited the cultivation of students' creativity and divergent thinking. This runs counter to the requirement of the information age to focus on the cultivation of information literacy, creativity and cooperative spirit. In the smart classroom, new learning methods such as autonomous learning and inquiry-based learning are advocated in learning methods, which not only increase students' interest in subject learning content, but also create a personalized learning environment in the learning environment through analysis of each student's learning situation , And expand the learning environment to the online learning space instead of being limited to the physical classroom environment. In this way, it promotes students' smart learning, and improves students' creativity, cooperation ability, and logical thinking ability. Therefore, the smart classroom not only meets the requirements of education informatization in our country, but is also the meaning of "student-oriented" and "development-oriented".

Based on the above analysis, this paper analyzes the intelligent engine of the Internet of Things platform, and builds an intelligent English learning system on this basis to improve the current English teaching effect.

2 RELATED WORK

At present, many universities have conducted a lot of research and development on the Internet of Things and Internet of Things control. The CENS laboratory, WINS laboratory, NESL laboratory, LECS laboratory, IRL laboratory, etc. of the University of California, Los Angeles have conducted research on IoT machine control [4]. The literature [5] designed some control systems to realize some wide-area control systems. The literature [6] has done a lot of research work in mobile self-organizing network protocol, application layer design of sensor network system, etc., and has achieved a lot of results in network protocol and control application in Internet of Things control.

The literature [7] mentioned a unified control management strategy, that is, in smart cities, the government adopts certain control management strategies to achieve unified management of public transportation, health care and public safety. Since it is managed uniformly by the government, it can reduce departmental redundancy. The management control strategy proposed in the literature [8] is actually a centralized management strategy, which is managed by a comprehensive management platform. If a problem occurs in a certain place in the city, the manager can adopt corresponding countermeasures. The literature [9] put forward the contradiction between network architecture and network QoS in smart cities. However, as to how to solve or optimize the contradiction between real-time control and network QoS in smart cities, it only proposes a hypothesis that real-time control is performed under normal network conditions, but it does not provide an actual detailed solution.

The load aggregation layer communicates with the dispatching center for measurement data and control instructions[10]. The load aggregation layer is the middle layer between the load and the dispatching center for data forwarding. The load aggregation layer transmits the information status uploaded by the load to the dispatch center, and analyzes the control strategy issued by the dispatch center to manage the load [11]. The literature [12] proposed and implemented a new distributed rule engine system based on message passing. The system implements the rule engine in a distributed computing cluster and handles the matching problem of a large number of rule sets and a large number of data sets in parallel and efficiently.

The Internet of Things control platform in the literature [13] integrates the scenarios of smart health, agricultural irrigation, musical fountain, smart parking, shuttle bus traffic, and smart home. The literature [14] realizes the perception of temperature and humidity, smog, PM2.5, AC parameters, traffic flow, and weather conditions. Moreover, it can control entities such as doors, lights, curtains, lawn sprinklers, and musical fountains, and it also implements functions such as natural language control (including voice recognition and voice synthesis), constant temperature fish tanks, and automatic watering spray. The control method implemented in literature [15] is a centralized control method. In the control mode, the bottom layer transmits the control requirements to the IoT cloud platform through the IoT gateway. After the cloud platform analyzes the control requirements, it issues instructions to the Internet of Things gateway, and then the Internet of Things gateway sends the control instructions to the specific control terminal to achieve specific control.the centralized control method described in literature can be employed in the realm of digital art installations. By using IoT gateways to transmit control requirements to a centralized IoT cloud platform, artists can manage and orchestrate the behavior of multiple interconnected devices and components within their artworks. This centralized control enables synchronized actions and coordinated responses, allowing for complex and intricate interactions between different elements of the installation.

Alibaba Cloud launched the IoT platform in 2017. The device-side SDK that provides multiple protocols such as MQTT, CoAP, HTTP/S not only meets the real-time requirements of long connections, but also meets the low power consumption requirements of short connections. Moreover, it connects to a large number of devices downwards and provides data APIs upwards. At the same time, it combines with Alibaba Cloud's own data processing services to empower IoT device data [16]. IoTHub[17] launched by Baidu is a fully managed cloud service for the Internet of Things, which can support the mainstream Internet of Things communication protocol MQTT. Moreover, it establishes a two-way connection between the IoT platform and the device. Gizwits IoT platform developed by Gizwits IoT Company [18]. The platform provides the ability to cover the entire life cycle of services from product definition, equipment debugging, Internet of Things application development, cloud development, etc., to intelligent hardware access to operation management. Moreover, it minimizes the developer's research and development costs through comprehensive SDK and API services, and helps developers to quickly build applications [19].

3 SELECTION OF THE RECEIVING NODE OF THE IOT COMPUTING ENGINE

As shown in Figure 1, within the range of the angle $\theta\left(0 \le \theta \le 90^{\circ}\right)$ between the line of the key node's longitude coordinates and the connection line between the node and the computing IED node of the destination query subnet, this paper uses formulas (1) and (2) to calculate the receiving node in the destination query subnet, that is, the node with the smallest NN value[20].

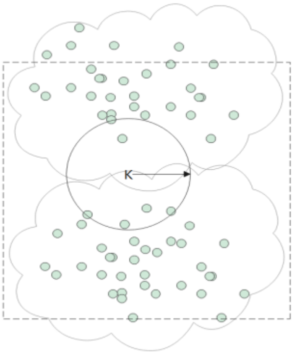

Figure 1: Schematic Diagram of the Selection of Receiving Nodes.

$$L_i = \begin{cases} \left|X_k - X_i\right| & \theta = 0 \\ \sqrt{\left(X_k - X_i\right)^2 + \left(Y_k - Y_i\right)^2} & 0 < \theta < 90^\circ \\ \left|Y_k - Y_i\right| & \theta = 90^\circ \end{cases} \tag{1}$$

$$NN = \arg\min\left(L_i\right), E_i \geq \varepsilon \tag{2}$$

The selected range is denoted by θ. The geographic location of the computing IED node has been determined during installation, namely:

$$node\_loc = \left\langle X_d, Y_d \right\rangle \tag{3}$$

1.When $\theta = 0$, that is, $Y_d = Y_k$, by comparing the size of X_i and X_k, it is decided to find the destination query subnet receiving node in the horizontal left or right direction. In the case of not finding it, we can increase the degree of θ in a small range and continue searching.

2.When $0 < \theta < 90^\circ$, the size of θ can be calculated by the following formula.

$$\theta = arc\tan\left|\frac{Y_d - Y_k}{X_d - X_d}\right| \tag{4}$$

When there is no sensor node in the range of θ, θ can be expanded to 2θ, and so on, the receiving node in the destination query subnet is continued to be searched.

3.When $\theta = 90^\circ$, that is, $X_d = X_k$, by comparing the size of Y_i and Y_k, it is determined to find the destination query subnet receiving node in the vertical upward or downward direction. In the case of not finding it, we can increase the degree of θ in a small range and continue searching.

We set to deploy n sensors in the grid, and periodically monitor the surrounding environment for data collection. The computing IED node is located in the center of the area. When s_i represents the i-th sensor node, the set of nodes is $S=\{s_i|1\leq i\leq n\}$.

The energy consumption of a node sending l-bit data to a location with a distance of d is[21]:

$$E_{Tx}(l,d)=\begin{cases} lE_{elec}+l\varepsilon_{fs}d^2 & d<d_0 \\ lE_{elec}+l\varepsilon_{mp}d^4 & d\geq d_0 \end{cases} \tag{5}$$

ε_{fs}、ε_{mp} is the energy required for power amplification in the two models respectively. Similarly, the energy consumption of a node receiving 1-bit data is:

$$E_{Rx}(l)=lE_{elec} \tag{6}$$

The distribution of sensor nodes, relay nodes and computing IED node is shown in Figure 2. Since this section only studies the data collection strategy of sensor nodes, and does not involve the storage method of sensory data, in order to make the description more intuitive, the storage IED node is not marked in Figure 2.

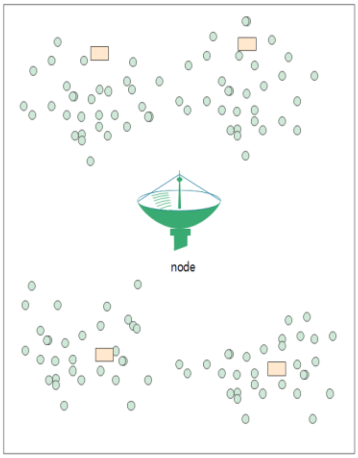

Figure 2: Distribution of Sensing Network Nodes in a Monitoring Area.

In this paper, the hierarchical clustering algorithm AGNES is used to divide the nodes in a monitoring area into several clusters based on the density, and each cluster elects the cluster head in parallel. The data transmission energy consumption of a node is closely related to distance. In the sensor clustering stage, the node first sends its position information to the computing IED node, and then the computing IED node divides the entire grid into multiple clusters according to the distance. It is stipulated that each node belongs to only one cluster, and the distribution of nodes in each cluster is relatively uniform. After the division, the computing IED node broadcasts the relevant information of the cluster division, and each node determines the cluster to which it belongs based on the broadcast information and its location. At the same time, in order to prevent over-fitting, the threshold $M, M \in (0,1)$ needs to be set, and the clustering stops when the ratio of the number of clustered nodes to the total is M. In this way, the relatively uniformly distributed nodes can be divided into a cluster, and the nodes in each cluster only need to perform local communication to campaign for the cluster head. Figure 3 is a schematic diagram of a grid clustering.

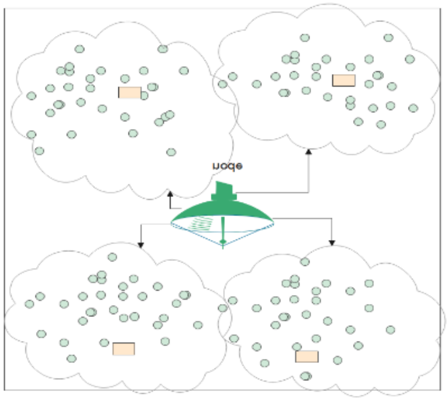

Figure 3: Schematic Diagram of Clustering of Sensor Nodes in a Monitoring Area.

As shown in Figure 3, after clustering, the nodes in the grid of Figure 2 are divided into 4 evenly distributed clusters. In the process of data transmission, the sensing nodes in the cluster transmit the data to the elected cluster heads. As for the sensor nodes outside the clusters, they are called outliers. During data transmission, the nearest cluster is selected and the data is transmitted to the nearest node in the area or directly to the computing ID node.

On the basis of clustering, in order to further optimize the energy consumption of sensory data collection and network transmission, this paper proposes a frequency-adaptive sensory data acquisition method. By analyzing the regression model, adaptively adjust the sampling frequency to achieve dynamic model update and compensation for missing data , Reduce data redundancy.

Figure 4 is a schematic diagram of the wireless sensor network structure in the cluster. Each sensor node SN can only communicate with its next hop node, so that the data is effectively forwarded to the cluster head node CHN along the path.

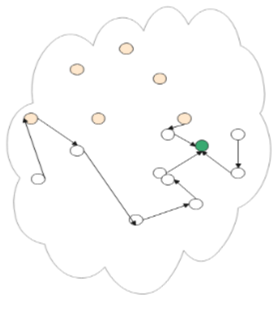

Figure 4: Schematic Diagram of Data Forwarding in a Cluster.

By analyzing the time series, it is found that when continuous sampling is performed, the perception information of a single sensor node in continuous time is similar or similar, that is, the collected data of the same node within a period of time has a high time correlation. Therefore, a univariate linear regression model can be constructed based on this feature to approximate the perception data. The dual prediction model is used, that is, the nodes in the cluster and the cluster head nodes use exactly the same model for data prediction, which reduces the amount of data transmitted. Figure 5 is a schematic diagram of a variable frequency acquisition model.

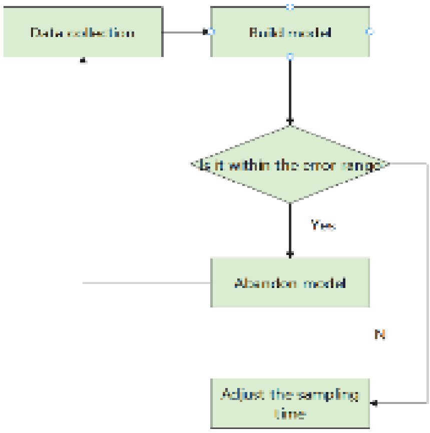

Figure 5: Schematic Diagram of Frequency Adaptive Acquisition Model.

As shown in Figure 5, after using the regression model to model the perception data on the sensor, each SN node transmits its regression parameters to the corresponding CHN node. According to the least squares function, the CHN node can use these parameters to calculate the regression model of each SN node in the cluster, so as to obtain the node's perception data. Before the model fails, the SN node does not have to transmit sensing data to the CHN node, which effectively reduces the amount of data transmission.

Due to the limited computing power and storage space of wireless sensor network nodes, this paper uses a one-element linear regression model to improve the prediction accuracy while reducing the complexity of the algorithm. Its form is:

$$\alpha' = a + bt \tag{7}$$

The collection of n sensing data sampled by nodes in the monitoring network in chronological order is denoted as:

$$TS = \{(t_1,\alpha_1),(t_2,\alpha_2),\cdots,(t_n,\alpha_n)\} \tag{8}$$

TS can be regarded as a univariate linear function with sampling time t as the independent variable and sampling data value a as the dependent variable. According to the least square method, a one-variable linear regression model can be fitted. In order to minimize the sum of squares of the error between the sampled data and the fitted curve, we set:

$$D = \sum_{i=1}^{n} d_i^2 = \sum_{i=1}^{n} \left[\alpha_i - (a + bt_i)\right]^2 \tag{9}$$

At the same time, in order to make the predicted data closer to the true value, D finds the second-order partial derivative of a and b, and the solution is:

$$\begin{cases} a = \bar{\alpha} - b\bar{t} \\ b = \dfrac{\sum_{i=1}^{n} t_i \alpha_i - n\overline{t\alpha}}{\sum_{i=1}^{n} t_i^2 - n\bar{t}^2} \end{cases} \tag{10}$$

According to the above formula, the SN node calculates the values of a and b as the parameters of the model and transmits them to the corresponding cluster head node. The cluster head node uses the received parameters a and b to construct a prediction model of the collected data of the SN node, and calculates the measured value of each node at each time point according to the model.

According to the time relevance of the sensing data, the sensing data is distributed around the prediction model along the time axis, and the optimization strategy can adaptively adjust the collection frequency, as shown in Figure 6. ε represents the error range, α represents the true value corresponding to the acquisition time t, and δ represents the difference between the predicted value and the true value, namely:

$$\delta = |\alpha' - \alpha| \tag{11}$$

T is the time interval for collecting data.

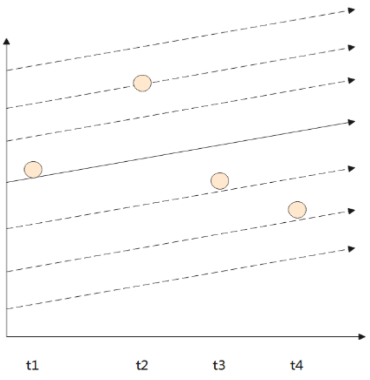

Figure 6: Schematic Diagram of the Unary Linear Regression Model.

As shown in Figure 6, the actual value of the sensing data will float within the error ε, and the initial value of the threshold $\beta(0 < \beta < \varepsilon)$ is $\varepsilon/2$. Then, the optimization strategy needs to meet the following rules in a certain period of time: Then the optimization strategy needs to meet the following rules in a certain period of time:

Rule 1: If $\delta \leq \beta$, it indicates that the time period model can meet the requirements well, and the sampling frequency can be reduced, and the model adjusts the collection interval $T = T + \Delta T$ linearly and adaptively (ΔT is 1 time interval unit). When $T = T_{\max}$, the threshold is $\beta = 1/2\beta$. By dynamically reducing the threshold value, continuous measurement at the maximum time interval can be avoided, which can improve the accuracy of data monitoring.

Rule 2: If $\beta \le \delta \le \varepsilon$, it indicates that the actual monitoring value has a tendency to deviate from the prediction model, the sampling frequency needs to be increased, and the model adaptively adjusts the collection interval $T = T/2$ in an exponential form. When $T < T_{\min}$, the periodic acquisition is performed according to $T_{\min}$. When $T = T_{\min}$, we set the threshold to $\beta = 2\beta$. By dynamically increasing the threshold, continuous measurement at the minimum time interval is avoided, which can reduce the energy consumption of the sensor.

Rule 3: If $\delta > \beta$, it means that the actual monitoring value deviates from the original model, and 4 data points are continuously collected according to h. If the 4 collected data deviate from the original model, the prediction model will be recalculated based on the 4 collected data. Otherwise, the collected data deviated from the original model is sent to the cluster head node CHN, and the original prediction model is retained.

In order to facilitate the generation of filtering tuples for node reduction, this paper generates query tuples $qdata\left(id, NLA(a,r), \max, \min, \mathrm{reg}\right)$ on the basis of normalizing the original data. Among them, id is the number of the node, and $NLA(a,r)$ is the normalized attribute value set of the original perception data. According to the following formula, the perception data is normalized to a value between $[0,1]$, and the attribute values of the perception data tend to be unified. The smaller the attribute value, the greater the control power, which is beneficial to the subsequent calculation of the filter tuple used to reduce the node. In the formula, a is the initial attribute value, and r is the attribute query range carried when the query is issued.

$$NLA(a,r)=\begin{cases} \left[a-MIN(r)\right]/\left[MAX(r)-MIN(r)\right], \\ a\text{'s}\exp ectation\ value\ tends\ to\ small \\ 1-\left[a-MIN(r)\right]/\left[MAX(r)-MIN(r)\right], \\ a\text{'s}\exp ectation\ value\ tends\ to\ big \end{cases} \tag{12}$$

α_i is the normalized value of a tuple attribute, n is the number of tuple attributes, max is the maximum value in $NLA(a,r)$, and min is the minimum value in $NLA(a,r)$, reg is the attribute space, which is the product of attribute values in $NLA(a,r)$. The calculation method is shown in the following formula:

$$\max = MAX\left\{\alpha_i \middle| \alpha_i \in NLA(a,r)\right\} \tag{13}$$

$$\min = MIN\left\{\alpha_i \middle| \alpha_i \in NLA(a,r)\right\} \tag{14}$$

$$reg = \prod_{1}^{n} \alpha_i \tag{15}$$

When the query is initialized, the sensing node in the query path uploads its own query tuple qdata to the cluster head node, and the cluster head node aggregates the collected qdata to form the TB_qdatas table. In order to quickly reduce the dominated nodes in the query path and reduce the data transmission in the network, this paper uses a small amount of calculations on the TB_qdatas table in the node to generate the filter tuple $fiter\_tuple(id, max\_m, min\_m, reg\_m)$ to determine the dominance relationship between the nodes. M is the set of max values of all tuples in the TB_qdatas table, N is the set of min values of all tuples, and R is the set of reg of all tuples. In the $fiter\_tuple$ tuple, id is the filter tuple number, max_m is the minimum value of the M set, min_m is the minimum value of the N set, and reg_m is the minimum value of the R set. The calculation method is as follows:

$$max\_m = MIN\left\{max_i \middle| max_i \in M\right\} \tag{16}$$

$$min\_m = MIN\left\{min_i \middle| min_i \in N\right\} \tag{17}$$

$$reg\_m = MIN\left\{reg_i \middle| reg_i \in R\right\} \tag{18}$$

In order to generate reduction tuples within the node, the filter_tuple needs to be uploaded to the parent node in the query path during the query initialization stage. The parent node itself and the collected filter_tuples of the child nodes form the TB_Sfilters table.

4 INTELLIGENT ENGLISH LEARNING SYSTEM BASED ON IOT COMPUTING ENGINE

This article builds an intelligent English learning system with the support of the Internet of Things engine technology. Based on the development trend of information technology, this research study defines e-schoolbags as a digital and intelligent learning environment with learners as the main body composed of teacher and student tablet terminals, learning resources and learning platforms, which support efficient "double English" development (online virtual English and offline actual English). The theoretical model is shown in Figure 7.

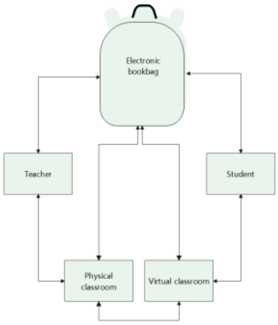

Figure 7: Architecture Diagram of E-Schoolbag.

This paper combines the relevant empirical research on the teaching mode and method of Smart English and the current situation of the development of Smart English in experimental schools to select two teaching contents, namely, the conversion of digits and the guidance of academic level examinations, to explore the design of smart teaching. After analysis, we found that the content of hexadecimal conversion teaching is relatively abstract and complicated, so traditional teaching methods can hardly resonate with students. At the same time, in order to avoid repeated teaching, save teaching resources, and improve teaching efficiency, personalized teaching is selected for practical research. The teaching design framework is shown in Figure 8.

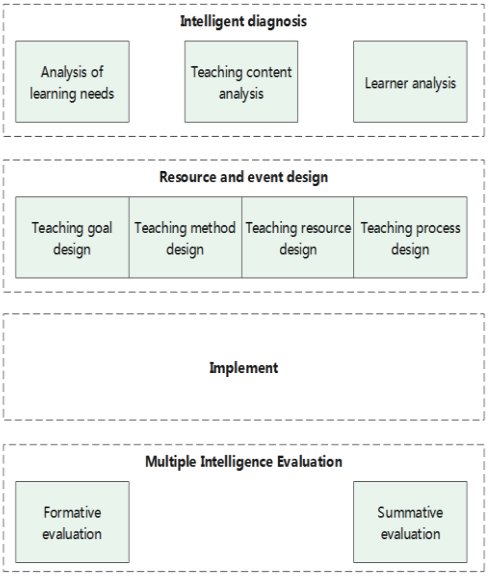

Figure 8: The Design Framework of Smart English Teaching.

The teaching process is the main part of the teaching design process. At the beginning of the design, it is necessary to use Smart English to predict the preparation of students, and then to design the inquiry activities according to the students' academic conditions.

5 EVALUATION OF THE EFFECT OF INTELLIGENT ENGLISH LEARNING SYSTEM

After constructing an English classroom learning system based on the next-generation computing engine of the Internet of Things, the performance of the system is evaluated. The system constructed in this paper is mainly used in classroom English teaching, and it combines the Internet of Things computing engine for data processing to improve teaching efficiency. Therefore, this paper uses experimental teaching to test the performance of the system, and sets up experimental groups and control groups to conduct teaching experiments. Before the teaching experiment started, the results of the two experimental classes and the control version are basically the same, and then the experiment teaching started. After a semester, the results of the two classes are counted, and the results are shown in Table 1 and Figure 9.

Number	*Experimental class*	*Control class*	*Number*	*Experimental class*	*Control class*
1	*99*	*97*	*31*	*74*	*72*
2	*98*	*97*	*32*	*73*	*70*
3	*97*	*97*	*33*	*72*	*70*

4	*96*	*97*	*34*	*72*	*69*
5	*96*	*96*	*35*	*72*	*63*
6	*95*	*96*	*36*	*72*	*62*
7	*95*	*95*	*37*	*71*	*62*
8	*95*	*94*	*38*	*70*	*60*
9	*94*	*94*	*39*	*68*	*58*
10	*94*	*92*	*40*	*67*	*55*
11	*93*	*92*	*41*	*67*	*55*
12	*93*	*91*	*42*	*65*	*54*
13	*91*	*91*	*43*	*64*	*54*
14	*91*	*89*	*44*	*64*	*53*
15	*90*	*89*	*45*	*64*	*53*
16	*85*	*88*	*46*	*63*	*53*
17	*84*	*86*	*47*	*62*	*51*
18	*84*	*85*	*48*	*61*	*49*
19	*84*	*84*	*49*	*60*	*49*
20	*83*	*82*	*50*	*60*	*49*
21	*81*	*82*	*51*	*60*	*48*
22	*81*	*81*	*52*	*59*	*48*
23	*80*	*81*	*53*	*58*	*46*
24	*78*	*79*	*54*	*58*	*45*
25	*77*	*76*	*55*	*57*	*43*
26	*77*	*74*	*56*	*57*	*42*
27	*76*	*73*	*57*	*57*	*41*
28	*76*	*73*	*58*	*57*	*39*
29	*75*	*73*	*59*	*57*	*38*
30	75	72	60	56	37

Table 1: Statistical Table of Test Results.

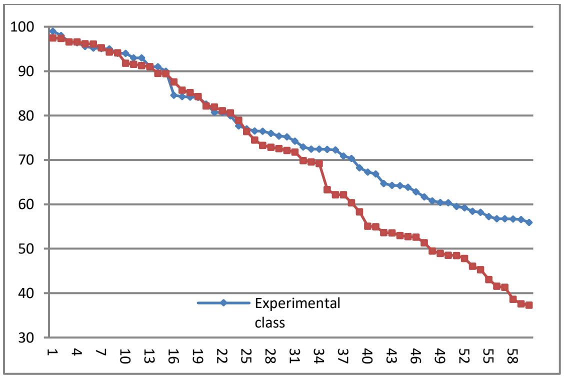

Figure 9: Statistical Diagram of Test Results.

From the comparison of the above results, there is a significant gap between the experimental group and the control group in the high segment. In the above 90 points segment, the experimental group is slightly better than the control group, but a large gap begins to appear below 75 points. It can be seen that the English classroom learning system based on the next-generation computing engine of the Internet of Things constructed in this paper has certain effects in English classroom teaching.

6 CONCLUSION

Smart classroom is a new type of classroom that deeply integrates information technology and classroom teaching. Smart classrooms can help teachers understand the learning situation of each student through the application of new intelligent technologies such as big data and learning analysis, but also better collect and integrate relevant teaching resources, so as to intelligently push the corresponding learning resources, pay attention to the learning situation of each student, and realize personalized teaching and cooperative inquiry teaching. Therefore, based on the next-generation computing engine of the Internet of Things, this paper builds an intelligent English classroom learning system on the basis of algorithm simulation. In addition, this paper constructs system function modules, and verifies the performance of the algorithm model of this paper through experimental teaching. The research results show that the teaching system constructed in this paper is effective.

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