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Research Article

Design and Application of Smart City Internet of Things Service Platform Based on Fuzzy Clustering Algorithm

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The development of the city is dependent on various information technologies, the core of which is the Internet of Things technology. The traditional multisource information collaboration mode of urban system is relatively single, with low collaboration efficiency and lack of effective measurement of collaboration structure. In this paper, a design scheme of IoT (Internet of Things) service platform for smart cities is proposed, and a multisource information collaborative difference measurement model with a given confidence interval is constructed based on a fuzzy clustering algorithm to meet the needs of developing IoT energy management application services and "smart city" energy management in different environments. In the experiment of participating in the fusion, the number of participating nodes is reduced to about 50 from the third iteration, which is reduced by half. In the traditional algorithm, almost all nodes participate in every fusion process. However, the improved algorithm can greatly reduce the number of participating nodes, thus greatly reducing the computational requirements of the algorithm. The experimental results show that the fuzzy clustering algorithm is effective. The system can be used in vehicle networking, geological disaster prevention, environmental monitoring, and other fields.

1. Introduction

As the trading center and gathering center of human beings, the city is the product of human economic and social development to a certain stage. The emergence of cities is a sign that human society has entered the civilized era, and it is also an advanced form of human social life. After 30 years of reform and opening up, China has entered a turning point, with a large number of people entering cities, especially large- and medium-sized cities. During the 12th Five-Year Plan period, China's urbanization rate exceeded 50%. Urbanization has promoted the development of the city, but it has also brought some problems that affect the further development of the city, such as dense population, traffic congestion, insufficient supply of urban resources, and bad environment [1].

The Internet of Things is a brand-new technology that evolved from traditional information technology and the Internet. It takes the Internet as the information carrier, connects all kinds of information devices to the Internet, breaks through the time and space constraints, and keeps people, machines, and things interconnected [2]. The practice of wisdom in cities is increasingly driven by a series of new information technologies, such as Internet of Things and cloud computing, and this dependence is irreversible [3]. Multisource information collaboration among different agents is the premise of the normal operation of a complex giant system. Under the traditional urban system, the multisource information collaboration mode is dominated by the central management mode, and the collaboration structure is relatively simple. In the application of complex giant systems in smart cities, the collaboration efficiency is relatively low. Traditional detection methods cannot accurately establish uniform detection features, which leads to the traditional detection methods that cannot detect the anomality of node data in the actual Internet of Things environment. We need to use information technology to help us manage cities more intelligently, improve people's quality of life, and solve urban problems in a unified way [4].

In recent years, the frequent emergence of large-scale data sets in various fields poses new challenges to cluster analysis research. Clustering analysis of large-scale data sets is generally considered from two aspects. On the one hand, a low-complexity algorithm is designed. In order to cluster large-scale data sets and deal with complex clustering, scholars have made a lot of efforts and put forward many new ideas. Literature [5, 6] proposed CLARANS (clustering large application based upon random search) algorithm. The algorithm does not deal with the whole data set but combines the sampling technology with PAM (Pulse Amplitude Modulation) and randomly selects a small part of the original data as the data sample. The algorithm is suitable for clustering analysis of large-scale data. Literature [7, 8] put forward an effective k-means clustering algorithm, which uses the distance between points and dormant clusters calculated in advance to reduce the amount of distance calculation and greatly reduce the running time and space used. In [9], a grid-based Wave Cluster algorithm is proposed. Using the multiresolution characteristics of wavelet transform, the algorithm can identify data sets with arbitrary shapes and sizes in the feature space of data. However, these proposed algorithms have some defects, such as random extraction of data sets and excessive subjective factors, which cannot reflect the global data information well and often produce poor clustering results.

The second section of this paper expounds the research status of smart city and Internet of Things technology. In the third section, the data preprocessing method of cluster analysis and object distance measurement, the data structure design method, and the confirmation method of data coding are put forward. The fourth section designs the intelligent city Internet of Things service platform. The fifth section verifies the effectiveness of this fuzzy clustering method in the construction of the smart city Internet of Things service platform. The fifth section is the summary of the full text.

The innovation of this paper is to study the difference structure measurement model and the network structure of multisource information collaboration by using the idea of fuzzy clustering and combining the advantages of condensed subgroups in relational clustering. On this basis, aiming at the problem that the traditional complex network community discovery algorithm is susceptible to noise and outliers, an efficient clustering ensemble algorithm for community discovery is proposed. Experiments show that the clustering ensemble algorithm can find complex network communities with high precision and high quality. Based on the fuzzy clustering algorithm, the difference measure model of multisource information collaboration with a given confidence interval is constructed, and the condensed subgroups and their relationships in the collaborative network structure are analyzed. The mode optimization strategy of multisource information collaboration is put forward from two levels of difference measure and relationship measure.

2. Literature Review

Jeon et al. [10] discussed the new challenges of information security in smart city environment by investigating the current situation of information security in smart city and summarized nine information security problems. Liu [11] put forward that a smart city is to plan the development of a city in an intelligent and innovative way, especially how to apply people's wisdom to the information of planning a good city. Wang et al. [12] pointed out the basic functions required by the next-generation Internet of Things platform, including horizontal and vertical support, heterogeneity, mobility, scalability, security, privacy, and trust. Cross-domain next-generation IoT platform can promote the establishment of new services and improve the efficiency level by reusing the deployment infrastructure. Tong et al. [13] studied the information security factors concerned by public participation in smart city crowdsourcing projects through empirical research and put forward corresponding countermeasures: protecting citizens' privacy from two aspects of information security technology and information protection laws and regulations; strengthening the continuous availability of information systems; carrying out information security education activities to improve the awareness of information security protection; designing an appropriate information security feedback mechanism to monitor the integrity of information.

Zhao et al. [14] think that the construction of smart city is to apply information technology to the system management of the city so that every part of the city can run cooperatively, provide better development opportunities for enterprises, and make citizens' lives more quality. Schieweck et al. [15] proposed that smart cities should include three levels: sustained and healthy economic development; harmonious and comfortable life; using scientific and technological means to make management more scientific, intelligent, and information-based. Hwang et al. [16] combined the information system characteristics, information security threats, and vulnerabilities of smart cities, explored the information system security protection scheme of smart cities, and enriched the concept of information security of smart cities. Kai et al. proposed a concurrency algorithm of fuzzy clustering partition of cloud resources based on multithreads, which optimizes the problem of high-dimensional matrix operation by transitive closure method and applies it to the strategy improvement of Hadoop scheduler [17]. Halder et al. proposed an adaptive fuzzy clustering resource scheduling and allocation algorithm [18].

Aiming at the intersection and correlation characteristics of information organization and information field, fuzzy clustering can give confidence interval while analyzing feature similarity, which is an effective method to study multisource information collaboration in urban system. Traditional detection methods cannot accurately establish uniform detection features, which leads to the traditional detection methods that cannot detect the anomaly of node data in the actual Internet of Things environment. Based on the idea of fuzzy clustering, this paper studies the difference structure measurement model and the network structure of multisource information collaboration, calculates the specific risk value of smart city with the information gain rate as the index weight, and puts forward the corresponding optimization strategy from the horizontal and vertical dimensions.

3. Method

Due to the spatiotemporal characteristics of the data of the Internet of Things [19], this paper adopts the method of parallel clustering between nodes and divides the data distributed in different nodes into the same equivalence class so that the equivalence class contains the data of multiple nodes. However, the data in equivalence class have the same location information after anonymous generalization, which hides the correspondence between records and nodes and blurs the specific location information of data.

3.1. Data Preprocessing Method of Cluster Analysis and Object Distance Measure

3.1.1. Clustering Common Data Structures

(1) Simple Data Matrix. Simple data matrix is the structural data based on each influencing element of the classified object. That is, there are M classified objects, and each object has n influencing elements, and its structural data matrix can be expressed as

$$\begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}. \tag{1}$$

(2) Difference Data Matrix. Difference data matrix is a matrix for building similarity between objects. Difference matrix is based on the simple data matrix. Mathematical algorithms such as Euclidean distance and Manhattan distance are used to obtain similarity data matrix between objects. The general form is as follows:

$$\begin{bmatrix} 0 & & & & \\ d(2,1) & 0 & & & \\ d(3,1) & d(3,2) & 0 & & \\ \vdots & \cdots & \cdots & 0 & \\ d(m,2) & d(m,2) & \cdots & \cdots & 0 \end{bmatrix}. \tag{2}$$

Among them, $d(i,j)$ is the difference between objects. The larger the value, the lower the similarity between objects, and the smaller the value, the higher the similarity between them.

3.1.2. Preprocessing Method of Clustering Data. In the process of clustering analysis, because the clustering objects usually contain multiple influencing factors, the order of magnitude and dimension of each influencing factor are different, which has a great influence on the clustering results. Therefore, it is necessary to standardize and preprocess the data of clustering objects. A data set is given as follows:

$$\begin{bmatrix} x_1 & x_2 & \cdots & \cdots & x_j & \cdots & x_n \\ 1 & x_{11} & \cdots & \cdots & x_{1j} & \cdots & x_{1n} \\ 2 & x_{21} & \cdots & \cdots & x_{2j} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ i & x_{i1} & \cdots & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ m & x_{m1} & x_{m2} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}, \tag{3}$$

where $k = 1, 2, \cdots, m$ is the number of objects, $X = (x_1, x_2, \ldots, x_n)$ is the influencing factor contained in each object, and x_{ij} is the specific value of each influencing factor.

3.2. Design of Data Structure for Data Coding. For data point $O(o_1, o_2, \ldots, o_d)$, find out the hyperrectangular sequence $U_1, U_2, \ldots, U_k$, which contains O point and only R_n data points in data set $X = \{x_1, x_2, \ldots, x_N\}$ at the same time. In order to realize the association coding design, the definition is as follows.

Using the theory of probability and statistics [20], the data structure of coding is designed, and the homomorphic label association coding of the Internet of Things model is improved. The data structure of coding is analyzed. Assuming that the probability density characteristic of data coding is q_{ij}^c, taking the data information flow c as the research object, the rate from the homomorphic label association point i to the node j is calculated, and the definition of homomorphic rate σ_i^c under intercell coding compensation is obtained as follows:

$$\sigma_i^c = \begin{cases} x^c i = s^c, \\ -xi = d^c, \\ 0, \text{other}. \end{cases} \tag{4}$$

In this formula, x^c is the traffic demand of data stream c processed by multiprocessors under the Internet of Things. In homomorphic label coding, code stream masking error occurs, which requires energy constraint compensation. The energy consumption in the existing time T of GPU node i is less than or close to the initial energy E_i, and then the correlation is used to select features. Based on the Pearson correlation, the correlation degree in each subset can be defined as

$$\text{Merit} = \frac{k r_{cf}}{\sqrt{k + k(x-1) r_{ff}}}. \tag{5}$$

A data point $v = \{v_1, v_2, \ldots, v_d\}$ falls into a grid unit $u = \{u_1, u_2, \ldots, u_d\}$ if and only if there is $l_i \le v_i < h_i$, $(i = 1, 2, \ldots, d)$ for each v_i.

The network unit structure design of fuzzy data-extended clustering based on probability statistics is shown in Figure 1. In Figure 1, all neighbor units of grid unit g are called g's neighbor set, which is denoted as $\text{NB}(g)$. The data object set $X = \{x_1, x_2, \ldots, x_N\}$ is mapped to the partitioned spatial grid to realize the design of the association coding data structure.

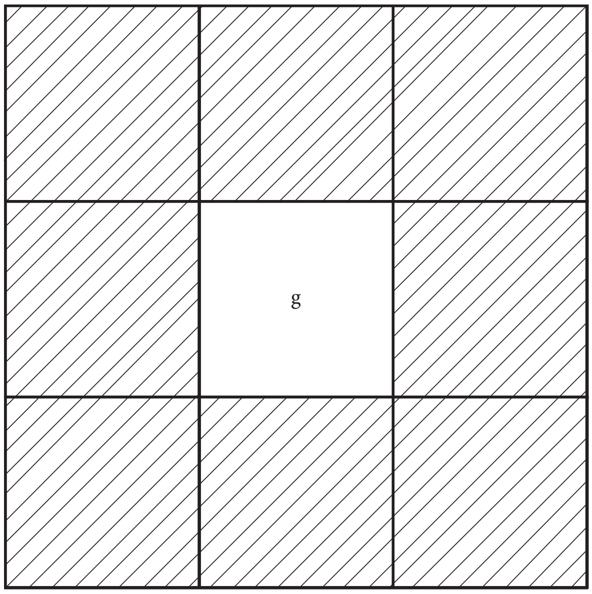

Figure 1: Network unit structure of fuzzy data-extended clustering based on probability statistics.

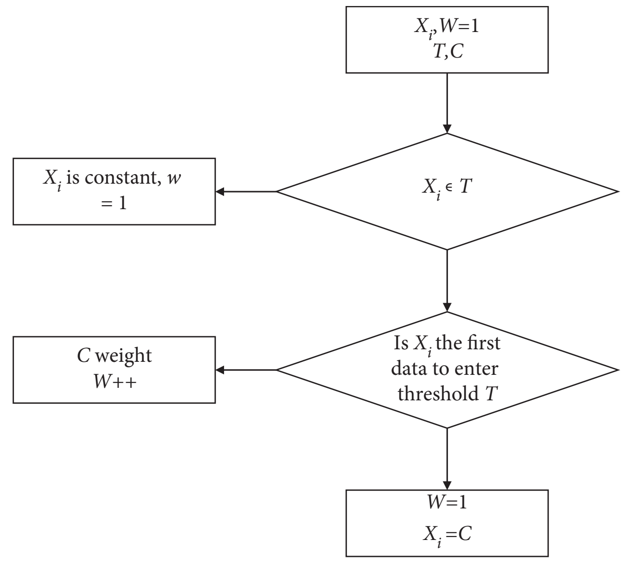

Figure 2: Flowchart of data discarding process.

3.3. Data Weight Value. For each data to be fused, the accompanying weight value is given as W. W is a positive integer with an initial value of 1. W expresses the data amount similar to this data, and the larger W is, the more data amount this data represents. $W = 1$ indicates that the data only represents itself.

When a certain data falls within the discarding threshold space, we discard it. However, if the amount of discarded data is too large, the calculation accuracy will often decrease [21]. Therefore, by introducing data weight, we give this data a certain chance to participate in the fusion again.

Giving the data the opportunity of reintegration is realized by modifying the fuzzy measure function.

Assuming that the number of sensors is n in the measurement environment and the actual number of sensors participating in a certain data fusion process is m, the fuzzy measure function is $M(A) = m/n$.

If the last fusion result is output as C and the weight of C is W after comparing all the data to be fused with the discarding threshold, then

If the data in the data group to be fused contains C, $M(A) = m/n$ will still be used.

Adjust $M(A) = (m + W + 1)/n$ if the data in the data group to be fused does not contain C.

According to the above ideas, the data discarding process flow of the improved algorithm is shown in Figure 2.

4. Design of Intelligent City Internet of Things Service Platform

4.1. Platform Architecture. The core of smart city is to use the new generation of information technology with the Internet of Things and cloud computing as the core in a more intelligent way. From the perspective of information technology, it is intended to achieve the purpose of efficient, accurate, and convenient urban operation by building a perfect and advanced intelligent system. Figure 3 shows the architecture of the system.

The Internet of Things service platform mainly includes front-end data collection system, middle-tier cloud computing data center, and back-end smart city applications [22, 23]. The overall architecture of the platform is designed as three layers, which are acquisition layer, service layer, and application layer, as shown in Figure 4.

The acquisition layer consists of massive distributed acquisition terminals. While the Internet of Things is widely used, it is also threatened by various influencing factors and harmful information in the external environment. If these pieces of harmful information cannot be controlled in time, it is likely to cause serious harm to all kinds of data acquisition equipment [24]. The service layer consists of information gateway and cloud computing data center. The information gateway receives multisource distributed sensor data in real time. Cloud computing data centers classify and store them and provide real-time data distribution services. The application layer displays the real-time state information of massive spatial targets in various platforms and ways and makes statistical analysis and application. Figure 5 shows the perceptual service model of information fusion management.

4.2. Independent Energy Management System Scheme. At present, in order to meet the needs of energy audit and energy management, an independent building energy management system (EMS) can be added to the building equipment management system (BMS), which is connected to the energy management platform of the Internet of Things through the BMS management platform. In this way, the independent energy management system can get rid of the limitation of the building equipment monitoring system, give full consideration to the setting of energy consumption metering points, and set the unified energy management function of the EMS server.

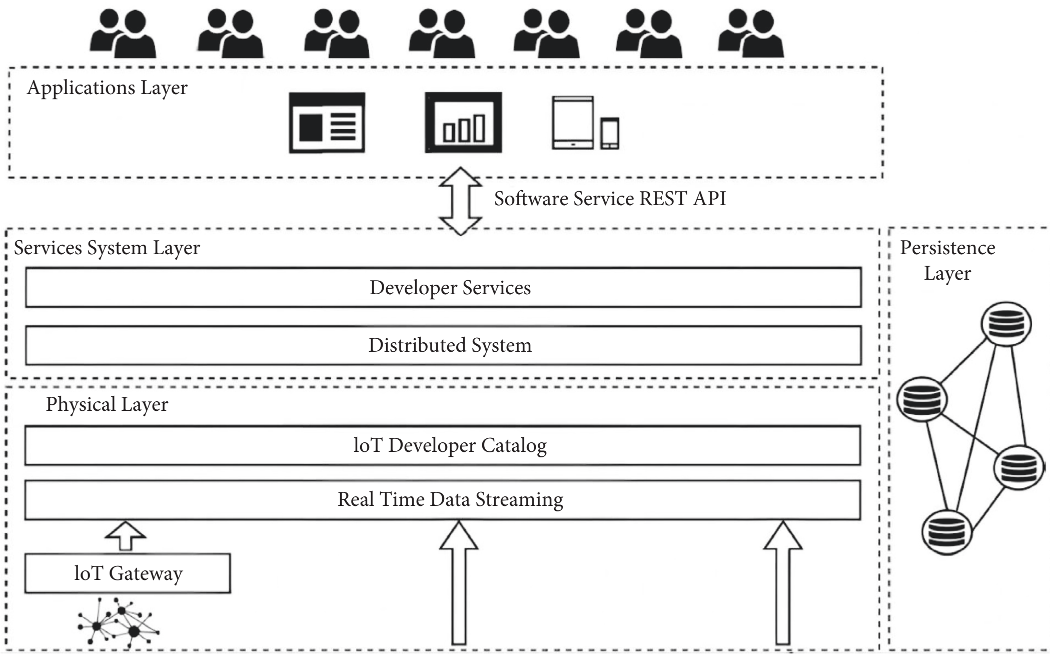

Figure 3: Smart city system architecture.

Aiming at the intersection and correlation characteristics of information organization and information field, fuzzy clustering can give confidence interval while analyzing feature similarity, which is an effective method to study multisource information collaboration in urban system [25]. If the energy management system is an independent system, the energy consumption in the building will be statistically analyzed. However, the lack of control and management of energy consumption equipment in buildings will only stay at the level of statistical energy consumption data, which is of little significance to building energy conservation. BMS system can realize the interconnection and linkage control among intelligent subsystems in intelligent buildings and can optimize the control of energy-consuming equipment according to the statistical analysis results of energy consumption.

Energy management system of intelligent building and other intelligent subsystems in the building may use a variety of different data communication protocols. OPC technology is used to enable users to access data through a consistent interface and integrate it into a unified BMS management platform for unified data analysis and management. Communication protocols commonly used in these systems are RS232, RS485, BAC net, Lon Works, Network API, Mod bus, SDK, DDE, and so on. No matter which protocol is based on, OPC technology can be used to access the integrated platform. The overall scheme of energy management system integration is shown in Figure 6.

After integrating the energy management system into the BMS platform, the energy management system in intelligent buildings can be accessed through the Web technology of the platform, the energy consumption data information of the energy management system can be read and analyzed, and then the equipment can be controlled and managed through the function of the building equipment monitoring system, so as to realize the sharing of information resources and unified control and management among all subsystems.

4.3. Infrastructure Construction Framework of Smart City. Digital technology in cities is mature and widely used, but the application of Internet of Things technology in surveying and mapping industry is still in the exploratory stage, and there is no unified standard [26]. The infrastructure construction of a smart city is the cornerstone of building a smart city information service system. At present, the typical representatives of smart cities in the world, such as Dubai, Malta, and Singapore, mainly use advanced information technologies such as telecommunications and IP networks to build science and technology parks and then transform them into industrial real assets, including significant asset management automation systems.

Advanced sensor configuration and programmable remote communication logic controller (PLC) are used to transmit network status within a predefined integrated framework supporting network operation platform to create a system, which can manage all assets and connect assets. GIS operation platform will become the foundation of infrastructure sensors and programmable logic controllers for managing the interoperability of all hardware/system-related systems. Focus on the existing public network to develop a comprehensive, universal, and standardized geospatial data model [27]. The network refers to the positioning of all network assets, such as pressurization, gravity pipeline, and valve system connecting all information, including connectivity asset rules.

Geographic Information System (GIS) can provide great support in allowing users to visualize characteristics and manage urban infrastructure network. This system will be

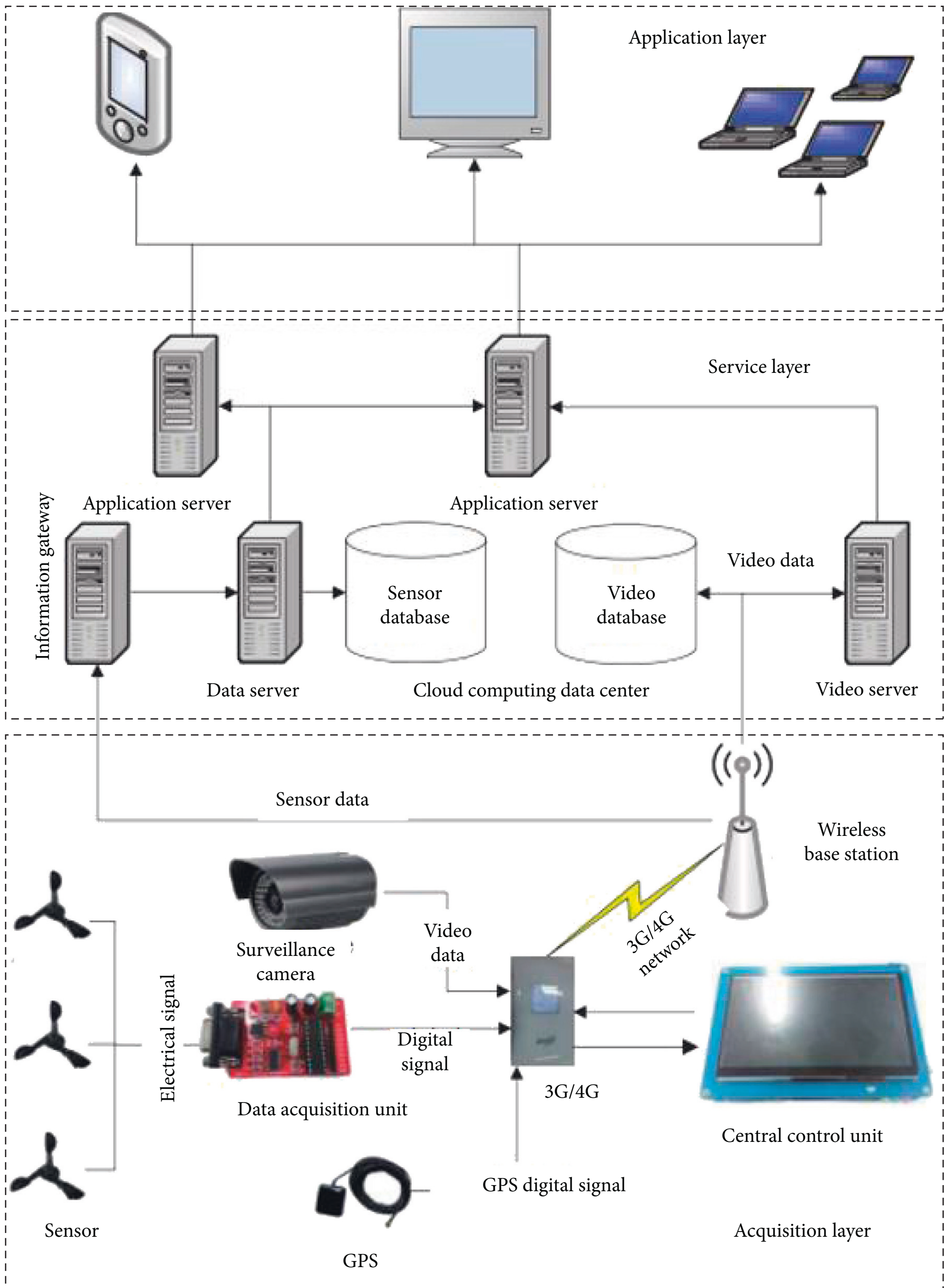

Figure 4: Overall platform architecture.

used to manage all available assets that are interoperable with all necessary/feasible systems in all aspects. Equipment management and tracking of all the space activities of the project will become the core aspects of the infrastructure construction of smart city information service system. Figure 7 represents the urban infrastructure renewal and communication with all relevant components.

4.4. Establishment of Related Government Data Storage and Index Structure. Based on the support provided by the EC2 (Elastic Compute Cloud) module for SQS (Simple Queue Service) operation of communication between different modules, query the qualified index value in the RDF data set index maintained by Simple DB through query statements, return the corresponding query result according to the index value, and output it to the front end through the query processor based on EC2 (Figure 8).

Index strategy and query processing algorithm of RDF data set in simple database use index to retrieve SPARQLquery related data sets and form query response through these data sets. This algorithm uses index to retrieve SPARQL query-related data sets and forms query responses through these data sets.

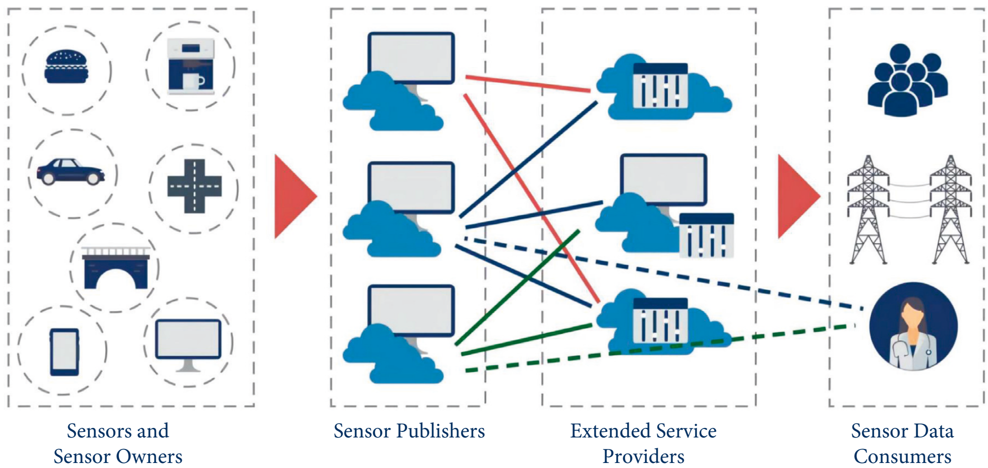

FIGURE 5: Awareness service model.

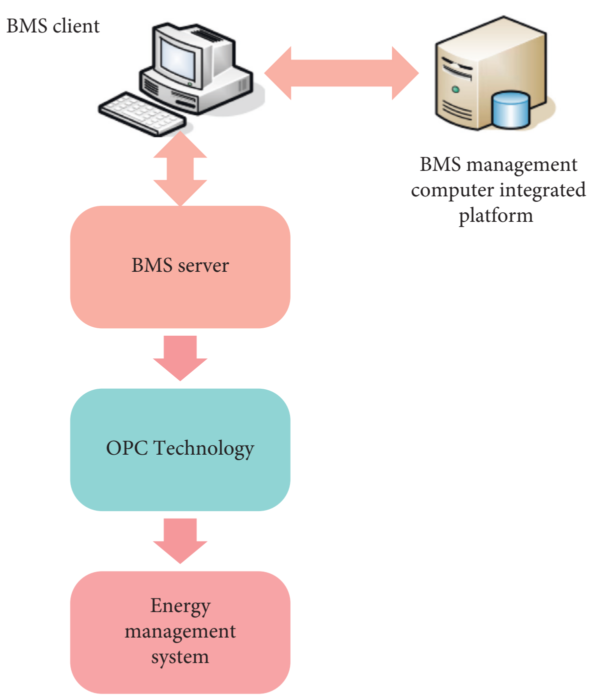

FIGURE 6: Energy management system (EMS).

This strategy creates three indexes for each data set: subject index, attribute index, and object index. Every index resides in a different Simple DB domain. Then, name an item name according to each data set and insert it into the corresponding domain. To facilitate access to RDF data sets stored in S3, the names of these data sets are also expressed by URIs. Therefore, using the defined label, the following index can be obtained:

$(S\,|U|\,S\,|S)$: use attribute-value pairs to enumerate the subject when the attribute name is "subject" and the attribute value is the subject.

$(P\,|U|\,P\,|P)$: use attribute-value pairs to enumerate attributes when the attribute name is property and the attribute value is property.

$(O\,|U|\,O\,|O)$: use attribute-value pairs to enumerate objects when the attribute name is "object" and the attribute value is object.

Simple DB has an upper limit of 246 manageable attribute-value elements for each item. This means that a given data set is limited to an independent item by this index strategy, which can only have 246 different subjects, 246 different attributes, and 246 different objects at most. Although it seems that there is not much problem with attributes in many cases, it will soon reach the upper limit for subject and object. Therefore, the system deals with this problem by assigning "partition" to the real data set URI and assigning a Simple DB domain to each data set.

4.5. Cloud Service Center. Cloud service center hardware mainly includes switches, database server hosts, database service slaves, staff station computers, projectors, printer backup uninterruptible power supplies, and other necessary hardware devices. When one server fails, the other automatically switches to the primary server. Users of this system can query and call data through the information publishing server after logging in to the system, instead of calling the data in the database directly, which can ensure the safety of the original data. System center software is divided into foreground client and background system administrator management client. The client is used by users to send instructions to control equipment, data query, statistical data, and other functions. The background is used by administrators to manage information such as system equipment, database, and users. After collecting abnormal feature data of IoT nodes, the abnormal probability of data nodes in IoT is calculated by combining feature fuzzy clustering so as to judge the specific number of abnormal data in IoT nodes. The data mining process in the cloud service center database is shown in Figure 9.

The interface and function of the system are designed for the existing urban facilities after a deep investigation and understanding of the existing drainage management system.

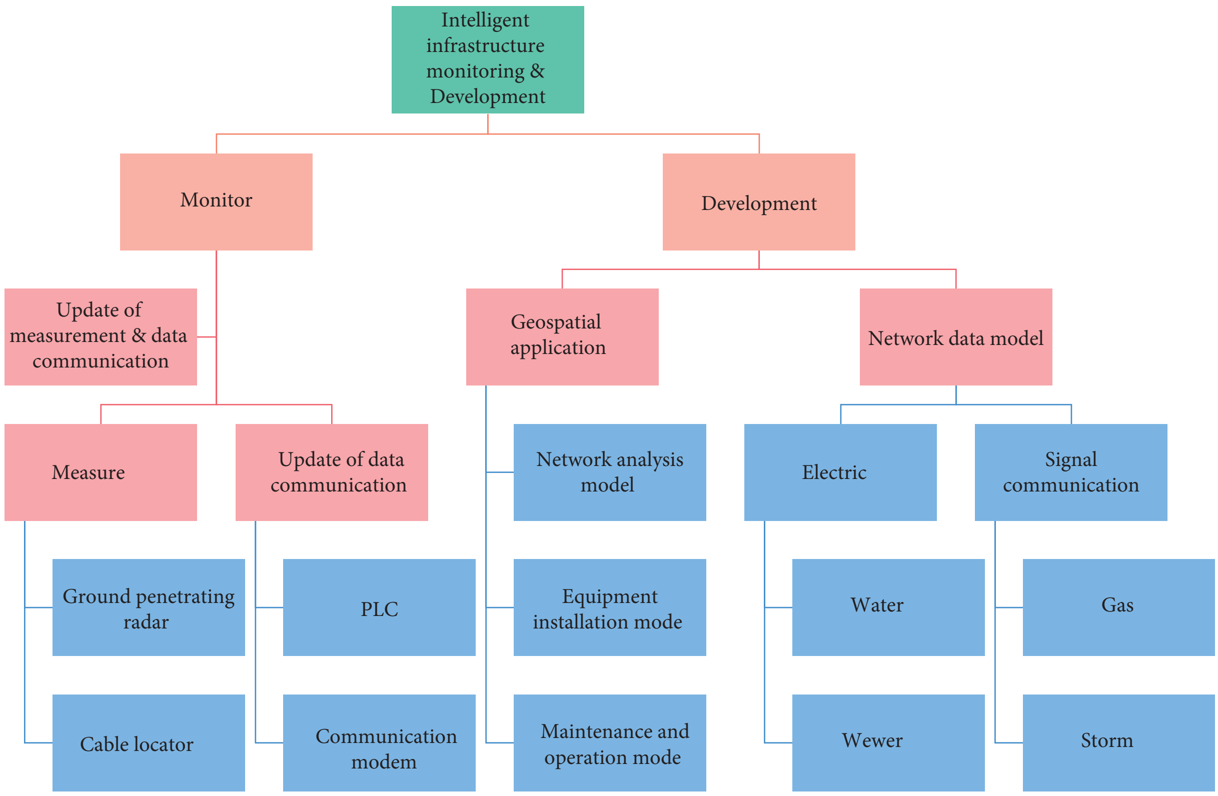

Figure 7: Infrastructure construction, resource development, and monitoring framework of smart city information service system.

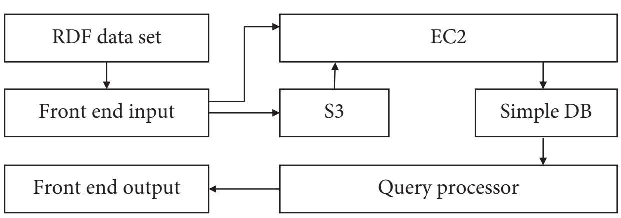

Figure 8: Data storage and index layer composition module.

The central website of the system is written in IIS + ASP language, with Windows 2003/2008/2010 as the central server operating system and SQL Server 2008 as the background database system software.

5. Applied Analysis

Based on the analysis of the algorithm principle, it can be seen that the actual number of effective nodes participating in fusion is an important index to measure the efficiency of algorithm improvement. The simulation experiment first counts the number of effective nodes participating in the two algorithms (the fuzzy clustering algorithm in this paper and the algorithm in literature [16]), and the results are shown in Figure 10.

The blue dotted line in the figure shows the number of nodes involved in the traditional fusion algorithm, which basically fluctuates slightly around 100. The blue dotted line is the number of participating nodes corresponding to the improved algorithm. Since the third fusion iteration, the number of participating nodes has been reduced to about 50, which is reduced by half. In the traditional algorithm, almost all nodes participate in every fusion process. However, the improved algorithm can greatly reduce the number of participating nodes, thus reducing the computational requirements of the algorithm to a greater extent.

While achieving the design goal of reducing the number of participating nodes, we also need to ensure the correctness and accuracy of the fusion results of the algorithms. For this reason, we compare the fusion results of the two algorithms, as shown in Figure 11.

The orange and blue dotted lines in the figure correspond to the fusion value fitting curves of the traditional algorithm and the algorithm in this paper. The comparison between the two shows that the accuracy and precision of the algorithm in this paper can meet the design requirements.

In practical work, the network communication ability of the system directly affects the choice of communication methods. In order to meet the application of various communication methods in the system, it is necessary to test the communication ability of various communication methods.

The test of the communication ability of WiFi wireless communication module is carried out without obstacles and with obstacles. The maximum value of its communication distance is determined according to the parameters provided by the manufacturer. The test results are shown in Tables 1 and 2.

The above test results show that when the outdoor is relatively open, the communication distance of WiFi is within 200 m, and when there are obstacles, the

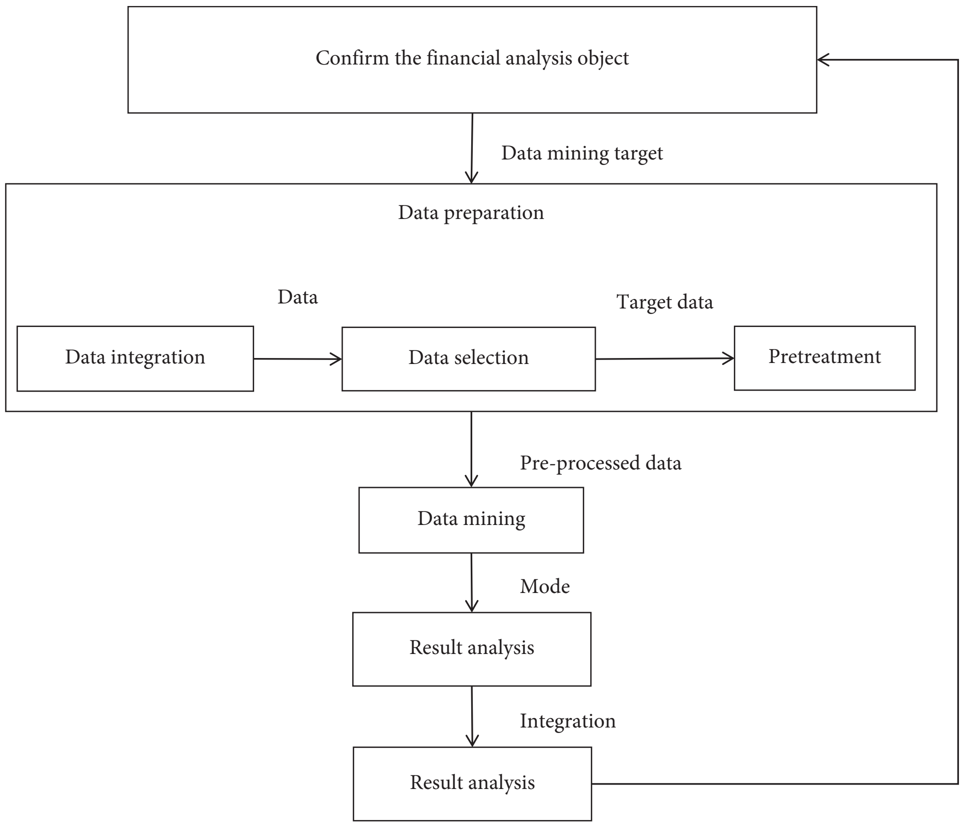

FIGURE 9: Data mining process in the cloud service center database.

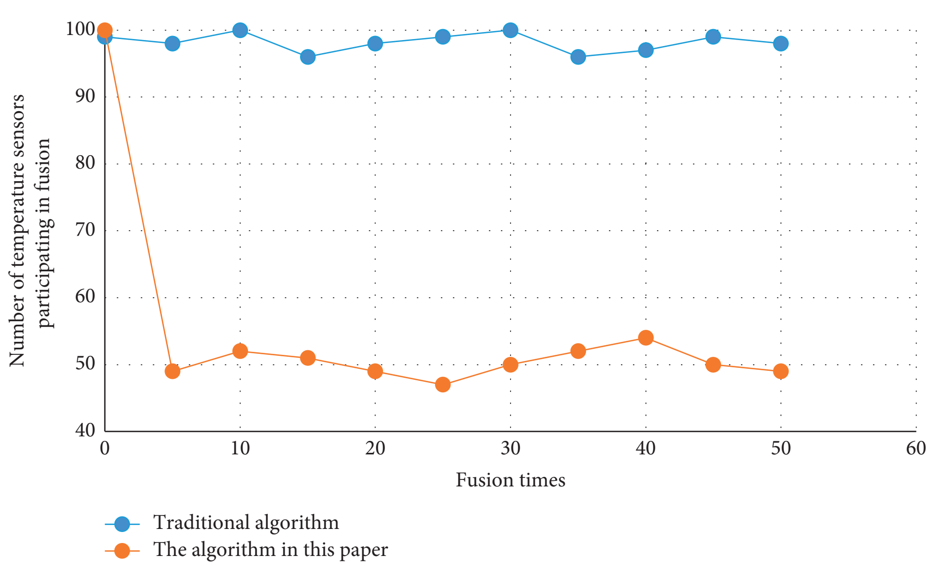

FIGURE 10: The algorithm in this paper effectively participates in the comparison of node numbers.

communication distance of WiFi is within 100 m, which is the best state.

In order to further prove the superiority of fuzzy clustering algorithm in information security risk assessment of smart cities, this paper introduces two classification methods, Naive Bayes and logistic regression, which are widely used in practice. The Naive Bayesian method is a classification method based on the Bayesian theorem and independent hypothesis of characteristic conditions, and logistic regression is a generalized linear regression analysis model. The two methods input the same data set (NSL-KDD data set) and the same cluster grouping to classify the risk level, and through 10% cross-validation, the results are shown in Table 3. The truth rate, precision rate, recall rate, F value, and ROC area in the table positively reflect the classification effect, while the false alarm rate negatively reflects the classification effect. We can see the fuzzy clustering algorithm from the table.

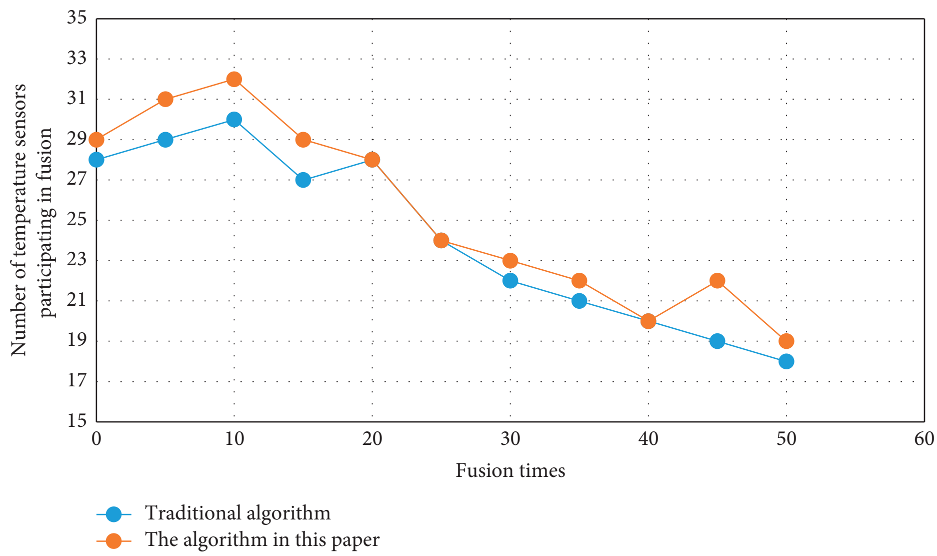

Figure 11: Comparison of fusion results of algorithms in this paper.

Table 1: Wireless communication capability test table of WiFi module without obstacles.

Module number	Test distance (m)	Antenna length (cm)	Networking status	Data transceiving	Test result
	150	6	Normal	Normal	Success
1	150	6	Normal	Normal	Success
	150	6	Normal	Normal	Success
	200	6	Normal	Normal	Success
2	200	6	Normal	Fail	Success
	200	6	Fail	Normal	Success
	250	6	Normal	Normal	Success
3	250	6	Normal	Fail	Success
	250	6	Fail	Normal	Fail
	300	6	Fail	Fail	Fail
4	300	6	Fail	Fail	Fail
	300	6	Fail	Fail	Fail

Table 2: Wireless communication capability test table of WiFi module with obstacles.

Module number	Test distance (m)	Antenna length (cm)	Networking status	Data transceiving	Test result
	50	6	Normal	Normal	Success
1	50	6	Normal	Normal	Success
	50	6	Normal	Normal	Success
	100	6	Normal	Normal	Success
2	100	6	Normal	Normal	Success
	100	6	Fail	Fail	Fail
	150	6	Fail	Fail	Fail
3	150	6	Fail	Fail	Fail
	150	6	Fail	Fail	Fail

The anomaly detection method of IoT nodes based on feature fuzzy clustering proposed in this paper can more comprehensively detect the anomaly data of IoT nodes and has a very important application value. It can effectively ensure the integrity of the detected anomaly data of IoT nodes, improve the detection efficiency, and then maintain the security of the IoT data transmission environment. In order to realize the unattended operation of the computer room and distribution system, remote monitoring of related equipment becomes more and more important. Through the data acquisition system of the energy management system, data collection and analysis of equipment are realized, and its running status and some important alarm information are uploaded to the operation control center in time so as to know the monitoring situation of front-end equipment in time, grasp the running environment of equipment and buildings in time, provide various early warning and postanalysis functions, and reduce the number of

Table 3: Comparison of the effects of three risk classification methods.

Appraisal procedure	True rate	False alarm rate	Precision ratio	Recall ratio	*F* Value	ROC area
Fuzzy clustering algorithm	0.891	0.023	0.895	0.883	0.879	0.902
Naive Bayes	0.68.3	0.117	0.650	0.694	0.613	0.733
Logistic regression	0.801	0.03	0.844	0.796	0.669	0.870

Table 4: Comparison between desktop cloud office and traditional office.

	Traditional desktop office	Desktop cloud office	Effect
Hardware equipment	1000 PCs	50 servers; 1000 thin terminals	Save 55% of costs
Office environment	Loud noise, high happiness, and fixed office	Mobile office with no noise and low emission	The environment is more friendly
Add new personnel	Purchase a new PC	Add virtual machine	Simple and economical
Maintenance efficiency	<100 units/person	>1000 units/person	Improve by 10 times
Equipment replacement frequency	3 years	10 years	Save 80% of expenses
Power consumption	300 W/h	12 W/h	Save 73% of electricity
Resource utilization	Computing resources are not shared, and hard disk storage is wasteful	Centralized and shared resources and dynamic adjustment of system performance	High resource utilization rate
Usability	High failure rate and easy loss of data	Low failure rate and centralized data storage and backup	High availability

inspections. The statistical analysis function of the system can generate various reports according to the needs, which is of great help to daily management and condition-based maintenance.

The administrative service center staff access the virtual desktop login interface through the desktop cloud client on the thin client, and the new employees register the virtual desktop. Administrators can enter the virtual desktop system through authentication after logging in to the virtual desktop management platform for approval. Administrators can schedule and manage the entire virtual desktop through the virtual desktop management platform. Compared with the traditional administrative office, the administrative service center designed in this paper adopts the desktop cloud office mode, and the results are shown in Table 4.

The application layer adopts a variety of data sources and integrates them organically, providing comprehensive statistical analysis operation and display functions. The adopted data can include sky map base map data, real-time video stream data, terminal GPS provided by cloud service, and various sensor data. Real-time sensor data can be displayed in various forms, such as text display, dashboard display, and real-time data line graph display. Dashboards and real-time line charts make the display effect more intuitive and have a good user experience effect.

6. Conclusion

The design of the IoT service platform has the characteristics of high availability and scalability, which can meet the needs of real-time collection, mass storage, and service distribution of multisource information in smart cities. In this paper, the fuzzy clustering algorithm is used to preclassify data, the decision tree algorithm is used to determine important risk factors, and the relative risk level of cities is evaluated. Information gain rate is used as index weight to calculate the specific risk value of smart cities. In the experiment of participating in the fusion, from the third iteration, the number of participating nodes is reduced to about 50, which is reduced by half. In the traditional algorithm, almost all nodes participate in every fusion process. However, the improved algorithm can greatly reduce the number of participating nodes, thus greatly reducing the computational requirements of the algorithm.

In order to fully develop the smart city model in a wide geographical scope, it is necessary to better understand related issues, such as required capacity, scalability, and interoperability, which are necessary to promote the faster development of innovative applications. In practical application, the structural measurement of multisource information collaboration needs to be combined with effective overall measurement methods to form a scientific evaluation of information collaboration level in smart cities.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The author declares no conflicts of interest.

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