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Monitoring and visualization application of smart city energy economic management based on IoT sensors

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Abstract

Urban economic development is not linear, but it always exhibits certain volatility. If the economic fluctuation exceeds a certain range, it may damage the urban economic development. In order to solve the economic damage caused by the excessive fluctuation of the urban economy in the development process, this article is based on the current situation of China's macroeconomic monitoring and early warning and data warehouse-related technologies, analyzed, explained the role of IoT sensors in the macroeconomic early warning system, reviewed the development process of economic monitoring and early warning, sorted out and compared several common economic monitoring methods, and proposed the application of IoT sensors to urban economic monitoring, the idea of early warning, and the construction of an urban economic data monitoring and early warning model. The urban economic data monitoring and early warning model is based on IoT sensors and has carried out research on data transmission, monitoring, forecasting, processing and display. After simulating the model, the results of the simulation experiment show that the accuracy rate of the economic volatility prediction of the model reaches 80%, which has certain practical value.

Keywords Internet-of-things sensors · Economic monitoring · Economic data · Dynamic display of data

1 Introduction

1.1 Research background of monitoring and visualization application of smart city energy economic management

Under the guidance of certain macro- and microeconomic theories, the monitoring and early warning of the economic cycle is based on the history and current situation of economic development, using corresponding forecasting techniques and methods to analyze and calculate economic statistics, study and understand economic laws. Economic development and changes determine whether the economic operating state is too cold, overheated or stable, and whether it is expanding or shrinking. It is produced in the process of commodity production and commodity exchange and develops with the needs of national economic policy formulation and enterprise economic decision-making. Forecasting is the basis for decision-makers to make decisions, and it directly affects the quality of decisions. Therefore, in the process of economic development, economic monitoring and early warning are very important. It has become a necessary research field for a country to develop its national economy and science and technology. It provides a scientific basis for individuals, enterprises and governments to understand future economic operations, judge development potential and formulate development strategies.

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1.2 Work related to monitoring and visualization application of smart city energy economic management based on IoT sensors

Today, the Internet of Things is an emerging technology that has been developed in many fields such as healthcare, smart home, agriculture, smart cities, education, industry and automation. Many sensors and actuator devices deployed in these areas can collect data or sense the environment. These data are further used to classify complex issues related to the specific environment around us, which also improves the efficiency, productivity, accuracy and economic benefits of the equipment. The main purpose of Ahirwar MK is how to process and classify the data collected by these sensors in IoT-based applications through classification algorithms. Ahirwar MK also identified classification algorithms with different parameters such as KNN, logistic regression and support vector machines, such as accuracy cross-validation, which were applied to the classification of large data sets generated by sensor-based devices in various IoT applications [1]. Sensor networks have expanded their scope and capabilities to become a basic part of the Internet of Things (IoT). In order to be able to meet interoperability requirements, it is necessary to build a repository of sensor data and observations. For this purpose, the Sensor Observation Service (SOS) has been created; however, since the last update a few years later, many technological changes have been accumulated. Pradilla J proposed and evaluated an SOS based on REST architecture and JSON-over-HTTP message exchange. The system is used for the interconnection of sensor networks, while improving the performance of these networks and promoting its deployment in the Internet of Things. The Internet of Things envisions some services that require both terminal device mobility and high availability or high bandwidth [2]. However, the current environment using cellular networks and single-path protocols may not guarantee sufficient service levels. Therefore, Sonntag S research evaluated the economic feasibility of using multi-path protocols to improve availability and bandwidth when contracting with multiple cellular operators. Through cost-efficiency analysis, Sonntag S has established a comparison model between multi-path protocols and its single-path solutions. The use of this model is demonstrated through two potential mobile application scenarios, which can benefit from improved availability or bandwidth [3]. Urban agglomerations have attracted the attention of city planners, economists and policy makers. In order to simulate urban agglomerations, Zhang R tried to establish a computable urban economic model combined with economies of scale through the method of new economic geography. Suppose that in a monopolistic competitive market, each firm produces a product variant, and the number of firms is clear and determined endogenously. The Dixit-Stiglitz utility function with product diversity is introduced into family behavior to reflect consumers' preference for varieties. On the other hand, internal increasing returns to scale and fixed costs are introduced into corporate behavior to expand the economies of scale of the model. Zhang R uses the extended clue model and the economies of scale to perform numerical calculations to explain and test how urban agglomerations are formed [4].

1.3 Research innovation

Based on the analysis of the status quo of China's macroeconomic monitoring and early warning and data warehouse technology, the role of IoT sensors in the macroeconomic early warning system is described, the development process of economic monitoring and early warning is reviewed, and several commonly used economic monitoring methods are sorted and compared. We proposed the idea of applying IoT sensors to urban economic monitoring and early warning, established an urban economic data monitoring and early warning model based on IoT sensors, and studied data transmission, monitoring, forecasting, processing and display issues [5]. The main innovations of this article are as follows:

This article introduces the architecture of the Internet of Things and then introduces the principles, functions and key technologies of each layer of the structure, the necessity of IoT data processing and the type of data processing [6]. It also describes the use and role of the Internet of Things in various fields. The analytic hierarchy process is used to construct a multi-level indicator system for monitoring and early warning, which embodies the three-dimensional thinking mode of multi-angle, multi-factor, multi-face and multi-measurement of the development of things.

By comparing various existing modeling methods of the early warning system, the comprehensive index method is determined as the index comprehensive method. Finally, according to the design principles of the economic early warning signal light system, various indicators were improved, the urban economic early warning limits and monitoring were analyzed, and a comprehensive early warning indicator was designed.

2 Data monitoring and forecasting dynamic display model of urban economic management based on IoT sensors

2.1 Wireless sensor network

Wireless sensor network (WSN) is an important interdisciplinary, cutting-edge and emerging research topic, including wireless communication technology, computer technology, software programming technology and information integration technology. According to specific application requirements, researchers first deploy sensor nodes in the surveillance environment. These nodes self-organize and collaborate in real-time perception and collection of information about observation objects within the network coverage area according to a specific protocol and then transmit the information in a multi-hop relay mode through the wireless communication network and then process it through the network. In an embedded system, the collected information will be transmitted to the end user. It can be seen that the wireless sensor network includes three important units: sensor nodes, monitoring objects and end users [7, 8]. The objective real world and the logical information world are connected through wireless sensor networks, which changes the way people communicate with nature, which will greatly improve the ability of mankind to understand and transform the world. Wireless sensor network technology includes relatively extensive research. According to the characteristics of wireless sensor networks, some of these technologies involve the media access control (MAC) protocol of the WSN data link layer, the routing protocol of the network layer, the system's energy-saving strategy, node positioning and time synchronization technology.

The structure of wireless sensor network is mainly divided into three types, namely hardware architecture, software architecture and communication architecture. The hardware architecture of WSN sensor node is mainly composed of four parts: information acquisition module, information processing module, communication module and energy supply module. The information acquisition module is mainly composed of sensors and A/D converters. Its main function is to sense and collect information through the sensor and then convert the information collected by the sensor into analog-to-digital conversion through the /D module.

The information processing module is composed of a microprocessor and a storage unit for calculating data. The microprocessor is equivalent to the control center in the node, and the storage unit provides storage space for the operation of the internal data of the microprocessor module in the node [9, 10]. The communication module is used to receive and receive data. In WSN, radio-frequency wireless communication is mainly used. Middleware management is used to control the devices included in the upper host middleware. The main function of the host middleware is to make each sensor node cooperate with each other, which is composed of virtual machines, services, components and algorithms. The main function of distributed middleware is to organize and coordinate services in the network system [11]. The main function of the client is to enable users to perform network configuration, send commands and query results in the client. The communication architecture of WSN is divided into application layer, transport layer, network layer, data link layer and physical layer according to the WSN network protocol. Among them, the application layer mainly refers to application layer service software developed in different application environments. The main function of the transport layer is error control and flow control, as well as the interconnection between WSN and the Internet [12].

2.2 Data analysis and processing of the Internet of Things

The Internet-of-Things system is currently very common, and it is used in many application areas. When the system runs in various application scenarios, it will collect various data. The importance of these data represents the purpose of the system in this application area. The data generated by the system has the characteristics of polymorphism, heterogeneity, quality and timeliness. When collecting data in the perception layer of the Internet of Things, different types of sensors will be used. Each sensor has different uses in different fields. There are many types of data, such as one-dimensional data, image and video data collected by cameras and other devices, and types of data generated by other devices. Therefore, the data are polymorphic. The polymorphism of the data and the heterogeneity of the perception model lead to the heterogeneity of the data [13, 14].

When monitoring and managing the Internet of Things, data are always generated continuously, which increases the amount of data. For example, the commodities in supermarkets usually reach tens of thousands or even millions. The system can track the goods through the electronic tags on the goods. In the process of continuous purchase by customers and continuous loading by employees, new data will be continuously generated, which makes the data in the system have the carrying capacity. When using the Internet of Things to manage traffic, it is necessary to keep track of the number of pedestrians and vehicles on the street to keep abreast of the latest traffic conditions. Because only the latest data can reflect the latest status of the monitored target, these data are timely.

Due to the above characteristics of IoT data, it is necessary to process IoT data [15]. The processed data can reflect the functions of the Internet of Things in the application field. Since the data collected by sensors, cameras and other hardware devices may not directly meet the requirements of managers, it is necessary to process the data so that the data can directly reflect the role of the data.

2.3 IoT sensor data prediction algorithm

Time-series forecasting technology has been paid attention to and widely studied by many scholars [16, 17]. In the course of development in recent decades, a relatively clear research branch has gradually formed, among which representative time-series data prediction methods are based on neural networks, support vector regression algorithms, correlation vector regression algorithms, grey models, etc.

BP neural network: ANN is a complex information processing system with learning ability. Its operating mechanism comes from the abstraction, construction, simplification and simulation of the real human brain structure and thinking process [[18]. The basic unit of artificial neural network is called neuron, which is similar to the structure of neurons in the human brain. Ann connects neurons layer by layer through a specific connection mode and constantly updates the connection weights and thresholds between neurons according to specific learning rules, so that they can learn the "input–output" relationship of any complex system. Due to the differences in the connections between neurons and the learning rules, many neural network models with different structures and functions have been formed, such as multilayer perception (MLP), back propagation neural network (BPNN), Hopfield neural network, random neural network, and the internet. As long as the expression is as follows.

Calculate the input and output of each neuron in the hidden layer in turn:

$$s_j = \sum_{i=1}^{m} w_{ij} x_i - \theta_j \tag{1}$$

$$b_j = f(s_j) \tag{2}$$

Calculate the input and output of each neuron in the output layer in turn:

$$l_t = \sum_{j=i}^{n} v_{jt} b_j - r \tag{3}$$

$$o_t = f(l_t) \tag{4}$$

Compare the expected output vector and calculate the correction error of each neuron in the output layer:

$$d_t = (y_t - o_t) f(l_t) \tag{5}$$

Calculate the correction error of each neuron in the hidden layer:

$$e_j = \left[\sum_{t=1}^{p} v_{jt} d_t\right] f(s_j) \tag{6}$$

In fact, the adaptive learning process of the BP neural network is a process of continuously adjusting and updating the connection weights and thresholds until they are determined. The system-related information obtained after learning is the determined connection weight and threshold [19, 20]. For new data samples, the predicted output value of the sample can be obtained by propagating the input vector from the input layer to the hidden layer and then to the output layer.

2.4 Multi-sensor network algorithm

Most of the research direction of multi-sensor network algorithms is to estimate the single transfer function vector of the network [21]. And in order to solve the real-time data processing in the network, many algorithms have been proposed. It includes consensus algorithm, incremental algorithm and diffusion algorithm. Multi-sensor network algorithm has good scalability and stability, which can make the network have the ability to learn and adopt [22, 23]. This method has been well applied to biological networks with complex and self-organizing behavior and can solve common optimization problems. The expressions are as follows:

$$\begin{cases} x_k = v_{k,i} \\ v_k = \mu_{k,i} \end{cases}, k = 1, 2, \ldots, n \tag{7}$$

For each node $k, (k \in v)$ in the upper structure, vector $x_k, i \in R^3$ represents the position information of node k at time i, and vector $v_k, i \in R^3$ represents the speed information of node k at time i [24]. According to the above formula, the position of node k at the next time i + 1 can be expressed as:

$$x_{k,i+1} = x_{k,i} + \Delta t \bullet v_k, i + 1 \tag{8}$$

For the entire sensor network model, the estimated cost function of a single node for the target position (using the mean square error criterion) can be expressed as:

$$j_k(w) = w^0 - w_{k,i} \tag{9}$$

The purpose of distributed processing is to obtain the best solution of the above formula only through local data, local collaboration and local multi-sensor network. Since nodes have a common goal w^0, an important issue is how to formulate a collaboration strategy so that each node in the entire network can obtain better results than each node through collaboration to obtain the best solution [25]. Another important issue is how to make the nodes in the network iterate continuously and exchange information flows with each other in real time.

3 Based on the Internet-of-Things sensor city economic management data monitoring and prediction dynamic display simulation experiment

3.1 Data sources

Based on sample data from 2010 to 2020, this paper predicts 32 specific indicators and economic growth quality monitoring and early warning indicators for 26 provincial capitals across the country in 2021 and provides early warning of the prediction results to realize the system's early warning function. In order to realize the warning function, it is necessary to determine the warning line and warning area. This article determines the average value of the absolute difference between the indicator sample value and its average value.

3.2 Data processing steps

(1) Original data collection: Different from ordinary nodes, the original prediction data columns of sub-cluster head nodes are divided into the prediction data columns sent and cached by ordinary nodes. Before the first prediction model runs, the sub-cluster head obtains the real data sent by the node as the original prediction data column.

(2) Normalization of data: Different evaluation indicators often have different dimensions and dimensional units. This situation will affect the results of data analysis. In order to eliminate the dimensional influence between indicators, data standardization is required. To solve the comparability between data indicators.

(3) The definition of early warning limits: Combine the critical values obtained by mathematical statistics with the critical values of various indicators given by historical data and adjust them to obtain the critical values of system early warning indicators.

(4) Data prediction: Ordinary nodes start to run the prediction algorithm in this article and use the collected actual data column to predict the next cycle of collected data.

(5) Comparison of prediction errors: Compare the predicted value with the data collected by the node. If the error is within a given threshold, the node does not need to update the data and prediction model, nor does it need to transmit the data to the sub-cluster head; otherwise, it will update the original prediction data column and send the actual data to the sub-cluster head node. The economic visualization of smart cities is shown in Fig. 1.

3.3 Data error handling

It takes the relative error between the predicted data and the sample data. If it is within a given threshold, the sink node will directly use the predicted data to send to the base station, and the node will not send the collected data this time. To prepare the forecast again, if the relative error is not within the threshold, the data collected by the node will be sent to the receiver node, and the data will be cached and the prediction model updated. Return to step to restart the forecasting process. It can be seen from the prediction process that the core of prediction data fusion is the prediction model. A good prediction model can not only reduce the energy consumption of the node running model, but also improve the prediction accuracy, reduce the transmission time of collected data, and save node energy. The smart city visualization combined with sensors is shown in Fig. 2.

4 Simulation experiment analysis

4.1 Simulation data processing analysis

As shown in Table 1, dividing economic prosperity into five different color areas can help us visually observe the current economic situation and formulate relevant macro-policies. The critical value that divides the signal light area, that is the maximum alarm limit, is a quantitative standard for judging the monitoring index and the overall prosperity state. The division of non-signal light areas and the determination of the early warning limit are another important factor in determining the scientific strength of the early warning system. The 15% quantile is the upper limit of the blue light area (the lower limit of the blue light area); the 30% quantile is the upper limit of the light blue area (the lower limit of the green area); the 25% quantile is the green light area, the upper limit (the lower limit of the yellow light area); the 45% quantile is the upper limit of the yellow light area (the lower limit of the red light area). According to the above-mentioned warning limit division principle, this article obtains the warning limit value of the five indicators selected.

The meanings of the five signal lights are as follows: Red indicates that the economy is in a booming stage and that the economy is overheating. Yellow means that the

Fig. 1 The economic visualization of smart cities (From http://alturl.com/oqfxx)

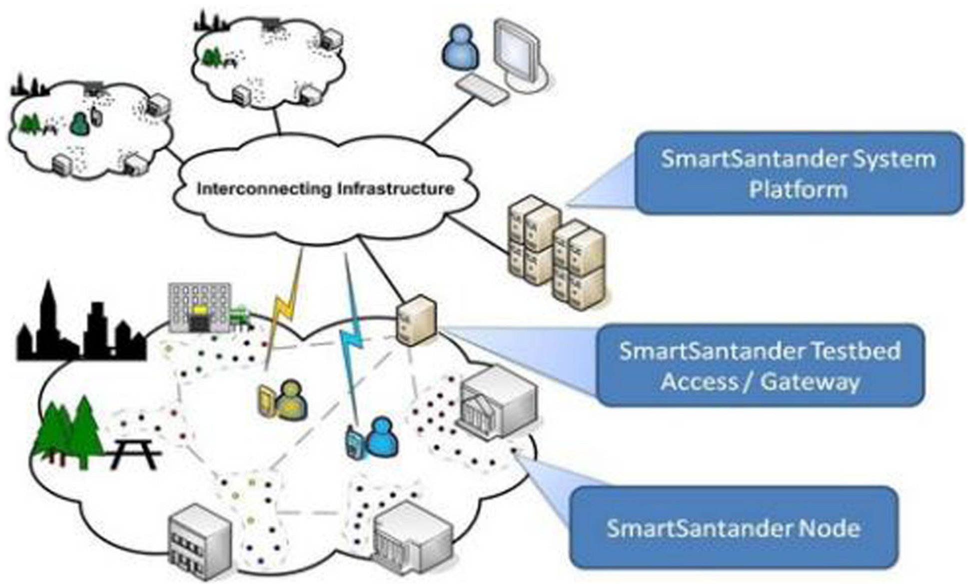

Fig. 2 The smart city visualization combined with sensors (From http://alturl.com/gdzdk)

Table 1 Early warning threshold value of each index

Index early warning	Overheated Red light	Thermotaxis Yellow light	Normal Green light	Cold tendency Light blue light	Supercooling Blue light
Indicator name					
Industrial output	96.2	75.3	86.4	48.2	66.8
Budget revenue of public finance	86.4	67.9	46.3	47.5	58.2
Total imports and exports	169.3	105.6	−63.2	-75.3	−126
Money supply	76.5	86.3	75.2	69.3	46.7
Completed fixed assets investment	127.4	28.9	47.3	37.2	9.7

economy is in a booming stage, and people always hope that the economy is in this stage. Red is rare in the part of economic early warning monitoring and analysis. This is the transition from overheating to economic prosperity. At this stage, it is difficult for the economy to maintain stability. Green means that the economy is in a relatively stable state and economic development is relatively stable. In the stable stage, the government can promote stable economic growth through fine-tuning of macroeconomic policies. Light blue indicates that the economy is in a period of recession, and the economy will tend to stabilize and shrink in the future. Blue means that the economy is very depressed, and the entire economic environment is in a period of depression or recession. At this time, the government should take strong measures to expand demand, expand employment, stimulate economic recovery and develop private cars.

4.2 Visual analysis of data monitoring and forecasting data

As shown in Fig. 3, the comprehensive early warning index trend group can determine the operating environment of each indicator based on the calculated critical value of each early warning indicator. By adding up the scores assigned by the different states of each indicator, a comprehensive early warning indicator can be obtained. The number of early warning indicators in this article is n = 5, the corresponding green line is 27, the limit of green and blue light is 32.7, the limit of green and yellow light is 62.5, the limit for light and blue light is 38.4, and the limit for yellow and red light is 35.7.

The standardized formula is as follows: Standardized early warning index = comprehensive evaluation score of the original early warning index/(3XN) X100, that is, the early warning index of W early warning index in the green area is 135, which is the most reasonable level, but W and the prosperity index can be linked together. Similarly, the critical value of each state of the early warning indicator can be divided by the number w to obtain the standardized critical value. The thresholds for standardized warnings are as follows: the green light line is 124, the limit for green and blue lights is 85.4, the limit for green and yellow lights is 89.7, the limit for blue and blue lights is 45, and the limit for yellow and button lights is 127.

As shown in Fig. 4, when selecting early warning indicators, we do not need to consider whether the indicator is the first indicator, synchronized indicator or lagging indicator. Instead, we must rely on statistical facts and use mathematical experience to evaluate some indicators closely related to the economy, count, and prosperity. However, we use the consistent curve and peak-valley correspondence between the comprehensive index and the comprehensive early warning index to test whether the early warning index is reasonable.

When selecting early warning indicators, we do not need to consider whether the indicator is the first indicator, synchronized indicator or lagging indicator, but rely on statistical facts and use mathematical experience to count some indicators closely related to the economy. However, we use the consistent curve and peak-valley correspondence between the comprehensive index and the comprehensive early warning index to test whether the early warning index is reasonable. By comparing the curve trend of the consistent comprehensive index and the comprehensive proactive index in the figure above, we can find that the consistency is 30. The fluctuation of the index is basically the same as the early warning composite index, and the wave trough and wave trough basically coincide. The correlation coefficient is 0.36 and the delay number is 0, indicating that the two have a good correlation. In summary, w believes that the selection of indicators for business monitoring analysis is more reasonable, and the compilation of comprehensive early-warning indicators is more scientific, which can achieve better prediction results.

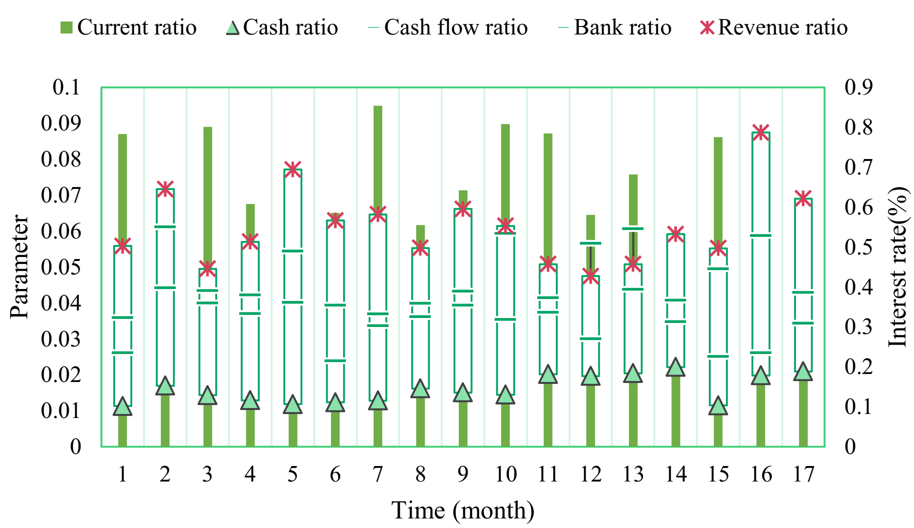

Fig. 3 Trend chart of economic comprehensive early warning index

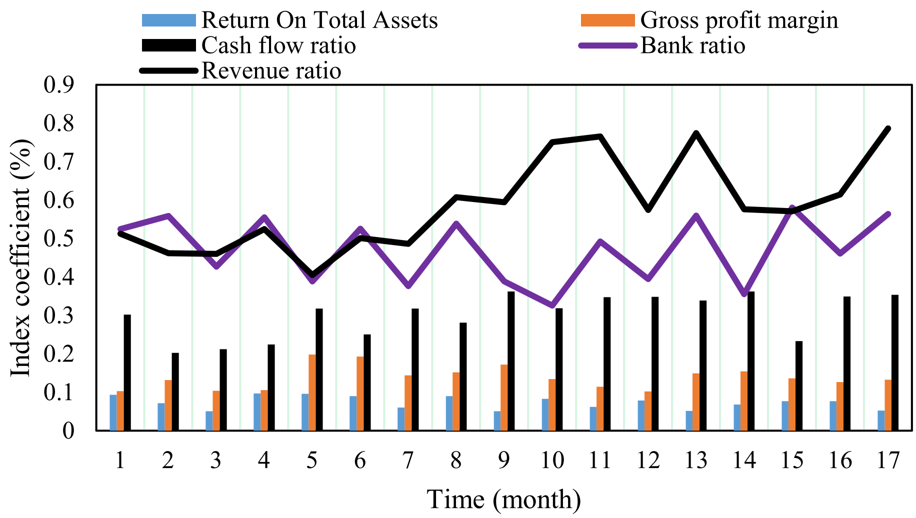

Fig. 4 Comparison of synthetic index and comprehensive early warning index trend

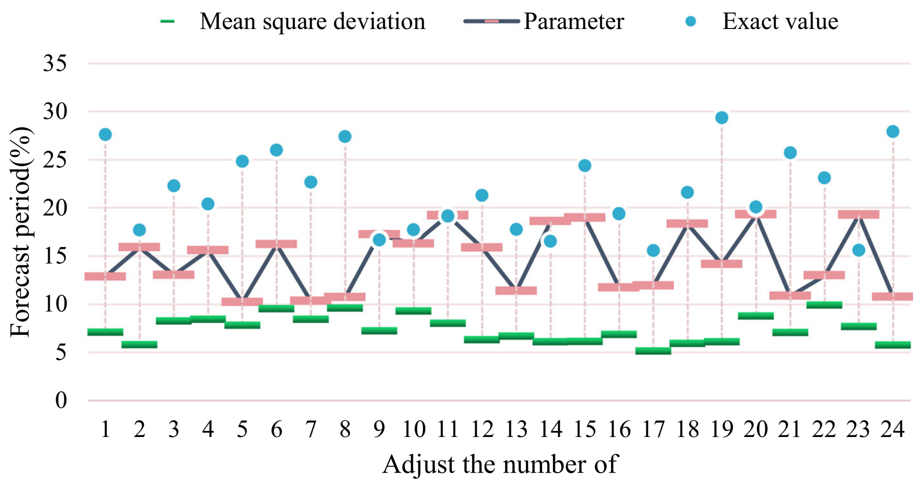

Fig. 5 Comparison of prediction results of different samples

4.3 Algorithm performance analysis

As shown in Fig. 5, due to the periodicity of perception data over time, this paper compares and analyzes the prediction efficiency when the sample size is 1000, 1500, 3000, and 6000.

The more data recorded, the more accurate the predicted data, that is, the smaller the mean square deviation, the larger the parameter. The prediction performance of the consensus algorithm is better than the other two algorithms. After 2015, the prediction accuracy of the data set size has been greatly improved. The prediction-based WSN data fusion algorithm is based on reducing the amount of data transmission in the network to reduce the overall energy consumption of the network and improve the network running time. Therefore, the amount of data transmission in the network is the most important criterion for measuring the sensor network algorithm based on prediction.

As shown in Fig. 6, the comparison results of the network data transmission volume per unit time of the three algorithms are shown. It can be seen from the figure that in the early stable stage of the consensus algorithm, the incremental algorithm and the diffusion algorithm, the network data transmission volume of each round of the three algorithms is 360, 720, 980 and 1650, respectively.

Compared with the incremental algorithm and the diffusion algorithm, the consensus algorithm can reduce network data transmission by 25%, 27% and 36%, respectively. It can also be seen from the figure that the incremental algorithm and the diffusion algorithm have almost no data transmission after the data processing sample is greater than 2000, which indicates that most network nodes are dead and no longer working. After the data sample is larger than 4000, the amount of data transmission in the network is greatly reduced, and a large number of nodes die. This shows that the algorithm in this paper greatly reduces the energy consumption of nodes and extends the life cycle of the network.

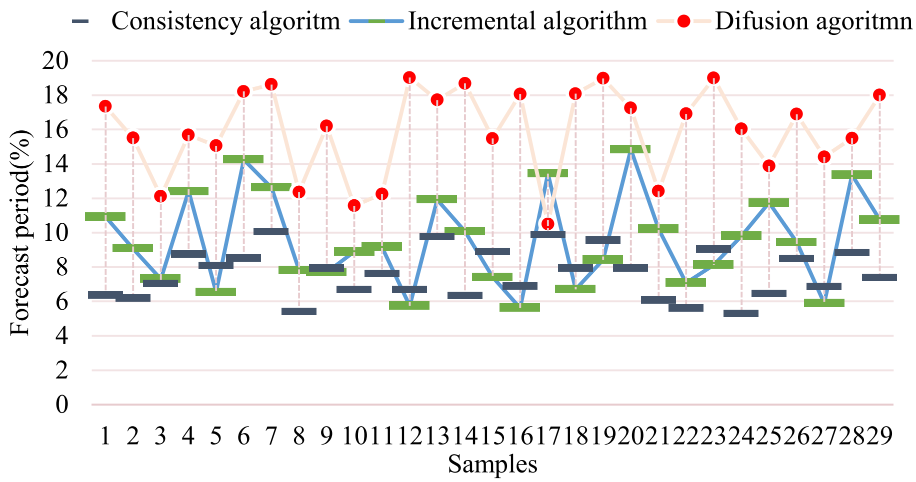

Fig. 6 Algorithm performance analysis diagram

5 Conclusion

In order to solve the problem of economic damage caused by the excessive fluctuation of the urban economy in the development process, this article analyzes the current situation of China's macroeconomic monitoring and early warning and data warehouse-related technologies and elaborates the Internet-of-Things sensors in the macroeconomic early warning system. It reviewed the development process of economic monitoring and early warning, sorted out and compared several common economic monitoring methods, proposed the idea of applying IoT sensors to urban economic monitoring and early warning, and built a model of urban economic data monitoring and early warning. The urban economic data monitoring and early warning model are based on IoT sensors and has carried out research on data transmission, monitoring, prediction, processing and display.

This article introduces the architecture of the Internet of Things and then introduces the principles, functions and key technologies of each layer of the structure, the necessity of IoT data processing and the type of data processing. It also describes the use and role of the Internet of Things in various fields. The analytic hierarchy process is used to construct a multi-level indicator system for monitoring and early warning, which embodies the three-dimensional thinking mode of multi-angle, multi-factor, multi-face and multi-measurement of the development of things. By comparing various existing modeling methods of the early warning system, the comprehensive index method is determined as the index comprehensive method. Finally, according to the design principles of the economic early warning signal light system, various indicators were improved, the urban economic early warning limits and monitoring were analyzed, and a comprehensive early warning indicator was designed. Finally, the consensus algorithm has the advantages of simple design, easy mastery and easy operation. Under the influence of multiple factors, the evaluation effect of complex issues is better. Since the macroeconomic operation has obvious consistency, in order to obtain more reasonable and satisfactory evaluation results, the consistency algorithm is a better choice. Secondly, the analytic hierarchy process is used to construct a multi-level indicator system for monitoring and early warning, which embodies the multi-angle, multi-factor, multi-faceted, multi-scale three-dimensional thinking mode of the development of things, and fuzzy mathematics. Proficiency in the use of membership as a bridge, the uncertainty of things into formal certainty, so that you can use traditional mathematical methods to analyze and monitor business cycle fluctuations.

The pressure of inflation on the economy will continue for some time. In the government's macro-control of the urban economy, the control of inflation has also been given top priority. On the one hand, structural inflation is caused by rising domestic labor costs and the prices of various primary products; on the other hand, the large fluctuations in exchange rates and raw material prices are affected by international factors such as the US quantitative easing policy, the Japanese earthquake and the turmoil in Libya. Finally, due to the availability of data and the limitations of the author's knowledge structure, this article still has many areas to improve. When we use actual data to monitor and warn the macro-economy, it will be more accurate if we use monthly or quarterly data to verify the effect. However, due to the limitations of index data, this article did not do so, which greatly reduces the early warning function of the system. The author will further deepen the research.

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Declarations

Conflict of interest There are no potential competing interests in our paper. And all authors have seen the manuscript and approved to submit to your journal. We confirm that the content of the manuscript has not been published or submitted for publication elsewhere.

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