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Low carbon energy industry and network economy prediction based on sensors and real-time data processing

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Abstract

As the global focus on sustainable development intensifies, the low-carbon energy industry has gradually become an important area to address climate change and achieve economic transformation. Developments in sensor technology and real-time data processing offer new opportunities for the energy industry to efficiently monitor and optimize energy use. This study explores the predictive ability of the low-carbon energy industry based on sensors and real-time data processing in the network economy, in order to provide data support for relevant decisions and promote the development of low-carbon economy. This paper uses sensor networks to collect real-time data in the process of low-carbon energy production and consumption, and combines big data analysis and machine learning algorithms to conduct dynamic modeling of industrial operation. Through the analysis of data under different scenarios, a prediction model is constructed to assess the development trend of the low-carbon energy industry and the impact of the network economy. The results show that the use of sensors and real-time data processing technology can significantly improve the forecasting accuracy of the low-carbon energy industry. The model forecast shows that with technological progress and policy support, the low-carbon energy industry will show a continuous growth trend, and will also play a positive role in promoting the development of the network economy.

Keywords: Sensor; Real-time data processing; Low-carbon energy industry; Network economic forecasting

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1. Introduction

Advances in sensor technology offer new possibilities for the monitoring and management of the low-carbon energy industry. Through a wide range of applications in the process of energy production, transmission and consumption, sensors are able to collect and analyze large amounts of data in real time. These data can not only help enterprises optimize production processes and improve energy efficiency, but also provide a scientific basis for policy makers to better promote the implementation of low-carbon policies and corresponding economic adjustments. The rise of the network economy has also injected new vitality into the development of low-carbon energy industry. The popularization of Internet technology makes the flow of information more rapid, data analysis and intelligent decision-making possible. Combined with real-time data processing and the network economy model, the low-carbon energy industry can achieve efficient allocation of resources, promote green innovation and development, and thus enhance the sustainability of the overall economy.

In today's digital age, IoT technology and sensor networks have become indispensable pillars in the economic field. With the rapid development of global economy and the continuous progress of science and technology, more and more equipment and goods are connected to the Internet, forming a huge Internet of Things system [1]. By analyzing big data, real-time data, and multidimensional data, network economy prediction models can help economists, decision-makers, and enterprises more accurately understand the laws of economic operation, predict market trends, and formulate effective policies and strategies [2]. The Internet of Things technology is a technical system that uses the Internet to connect with various sensors, devices and other items to achieve information sharing and intelligent control [3]. Through the Internet of Things technology, the interconnection of various items is achieving real-time data collection, transmission, and analysis, thereby promoting the development of intelligent applications and services. The Internet of Things technology enables the collection and transmission of large-scale data by connecting various items and devices [4]. This data can be used to construct network economy prediction models, helping economists and decision-makers analyze market trends, consumer behavior, etc., and providing a basis for decision-making. By utilizing IoT technology and sensor networks, we can better understand the laws of economic operation, predict and respond to market changes, and promote sustainable economic development and innovation.

By conducting in-depth research on the relationship between Internet of Things technology, sensor networks, network economy prediction, and decision models, we can deepen our understanding of the development of today's digital economy. The continuous progress and application expansion of IoT technology and sensor networks make it possible to collect and transmit large-scale data [5]. The analysis and utilization of this data can provide theoretical support and practical guidance for enterprises, governments, and decision-makers. In terms of network economy prediction models, the application of IoT technology and sensor networks can provide rich data sources [6]. By collecting and analyzing large-scale real-time data, more accurate predictions of market trends, consumer behavior, and competitive trends can be made. These predictive models can help enterprises formulate wiser business strategies, optimize resource allocation, and improve market competitiveness. In terms of decision-making models, the application of IoT technology and sensor networks can provide real-time and accurate environmental data, which can be used to evaluate the impact of environmental factors on economic development and help decision-makers formulate sustainable development policies and plans [7]. For example, by monitoring environmental parameters such as meteorology, soil, and water quality, we can better understand resource utilization and environmental protection needs, thereby providing scientific basis for decision-makers and promoting economic development and social progress. The Internet of Things technology and sensor networks inject new vitality and momentum into economic development and social progress in network economy prediction and decision-making models, achieving the goals of intelligent economy and smart society [8]. Therefore, in-depth research on the relationship between Internet of Things technology, sensor networks, network economy prediction, and decision models can grasp the development trend of today's digital economy.

2. Related work

Low-carbon energy industry refers to energy production and consumption activities aimed at reducing greenhouse gas emissions, including the development and utilization of renewable energy sources (such as solar, wind, water and biomass energy). With the increasingly serious problem of global climate change, countries have formulated policies to promote the transformation of low-carbon economy. According to the International Energy Agency (IEA), investment in renewable energy has grown steadily in recent years, and global renewable energy use is expected to rise significantly by 2030, becoming an important driver of emerging economic growth. In recent years, sensor technology has been applied more and more widely in the low-carbon energy industry. Sensors can be used to monitor various parameters such as temperature, humidity, flow and voltage during energy production, storage and consumption, providing real-time data. These real-time monitoring data can not only help enterprises optimize energy management and improve operational efficiency, but also provide decision support for policy makers. The literature shows that the deployment of sensor networks can significantly improve the intelligence level of renewable energy systems and promote the development of distributed power supplies and microgrids. The development of real-time data processing technology provides more possibilities for the low-carbon energy industry. Traditional data processing methods are often unable to cope with the needs of large-scale, real-time data analysis, while modern data analysis technologies, such as big data analysis and machine learning, can process and analyze data from different sensors in real time, mining valuable information. For example, the researchers used machine learning algorithms to assess the potential of wind and solar energy resources to optimize energy production strategies. The application of real-time data processing not only improves the efficiency of energy utilization, but also promotes the innovation and development of low-carbon technologies.

The rapid development of network economy provides new opportunities for the transformation of low-carbon energy industry. With the popularization of Internet technology, information sharing and data circulation have become more efficient, which has prompted major changes in the business model of the low-carbon new energy industry. For example, energy trading platforms based on blockchain technology allow users to trade electricity directly, increasing the transparency and efficiency of the energy market. Many studies emphasize that the network economy can promote the creation and exchange of low-carbon energy products, thus injecting new vitality into the low-carbon economy. Although some progress has been made in the research of the combination of low-carbon energy industry, sensor technology, real-time data processing and network economy, the large-scale application of sensor data has put forward higher requirements for data processing capacity and information security. On the other hand, issues of standardization and interoperability between different energy systems still exist, which may affect the overall efficiency of the system. Future research directions should focus on how to further optimize the combination of sensors and data processing technology to improve the intelligence level of low-carbon energy industry. In addition, the interdisciplinary cooperation will also promote the innovation and application of technologies and accelerate the sustainable development of the low-carbon energy industry.

According to the specific application scenario requirements, commonly used wireless communication technologies such as WiFi, Zigbee, and Bluetooth can be selected in the literature [9]. Each wireless communication method has its own characteristics and scope of application, and when choosing, it is necessary to comprehensively consider factors such as communication distance, power consumption, bandwidth, etc. Common processor architectures include ARM, MIPS, etc [10]. Choosing the appropriate processor requires consideration of performance, power consumption, cost, and other aspects. In addition, to improve the computing power and processing speed of the gateway, it is possible to consider using multi-core processors or processors that support multi-threaded processing. In the selection of embedded operating systems, literature uses popular embedded operating systems such as Linux, FreeRTOS, Zephyr, etc [11]. These operating systems have good reliability and stability, and have rich development resources and ecosystem support, making it convenient for developers to develop application programs and debug systems. The collection terminal is responsible for communicating with perception devices, collecting perception data, and performing preliminary processing and storage. Various sensors and actuators can be used to obtain environmental information and control external devices. The gateway sub platform is responsible for connecting the collection terminal and the monitoring center, processing perception data and converting protocols [12]. At the same time, the gateway sub platform can provide local data storage and caching, device management, security authentication and other functions [13]. As the core management node of the entire Internet of Things system, the monitoring center is responsible for receiving data from gateway sub platforms, conducting data analysis and decision-making, and providing feedback to the application layer. The monitoring center can also provide user interface, remote management, and control functions. In order to achieve the characteristics of low power consumption and energy conservation, the wireless sensor network in the literature adopts some technologies and methods that can effectively reduce energy consumption [14]. For example, nodes can enter low-power standby mode during idle hours to save energy, and regularly coordinate and transmit data between nodes, avoiding unnecessary communication overhead. Meanwhile, by optimizing communication protocols and data transmission mechanisms, energy consumption has been reduced. Collaborative operations are carried out between nodes to autonomously form clusters and elect cluster head nodes, achieving distributed network management and control. This self-organizing mechanism can adapt to changes in network topology and node failures. The literature proposes the low-power adaptive cluster layering protocol LEACH. The LEACH protocol introduces a random rotation mechanism, allowing each node to have the opportunity to serve as a cluster head node, balancing energy consumption and node load [15].

The ZigBee technology in the literature has the characteristic of low power consumption [16]. Sensor nodes can enter sleep mode when communication is not required to save energy. In addition, ZigBee technology utilizes a low-power listening mechanism that only communicates when necessary, reducing energy consumption. This makes ZigBee technology very suitable for sensor network applications that require long-term operation and limited energy. Although the communication speed is relatively low, it is sufficient to meet the needs and provide reliable communication connections for many low data rate applications, such as IoT devices and smart homes. The LoRa technology in the literature adopts a low-power modulation scheme, which can achieve longer transmission distances in complex environments such as urban and rural areas [17]. This is because LoRa technology utilizes low-power, broadband, and long time slot modulation methods, allowing signals to remain stable and reliable during long-distance transmission. This provides a wider coverage range and more flexible deployment methods for IoT applications. In the literature, the leapfrog algorithm is introduced for node redeployment [18]. The frog jumping algorithm is an optimization algorithm that simulates the natural behavior of frogs searching for food [19]. It searches for the optimal solution through a series of jumps. In node redeployment, the combination of frog jumping algorithm and local search of subgroups can effectively improve node connectivity and coverage. The literature initializes wireless sensor network nodes and solves irregular areas using the calculus method to obtain the optimal node configuration scheme [20]. By using the leapfrog algorithm to redeploy nodes, the distribution of network nodes can be more uniform, thereby improving the coverage and connectivity of the network.

3. Intelligent gateway system based on IoT technology and sensor networks

3.1. Design of Intelligent Gateway System

As shown in Figure 1, the LoRa module and vibration acquisition terminal of the gateway platform are the core components of the wireless sensor network. The LoRa module of the gateway platform serves as the main control center for the entire wireless sensor network, responsible for tasks such as network establishment, coordination, and maintenance. The number of vibration acquisition terminals is variable and managed by the LoRa module of the gateway platform, which can dynamically join or exit the network without affecting the operation of other terminals. The goal of the entire wireless sensor network is to achieve data collection and transmission, transmitting data from the perception layer to the network layer.

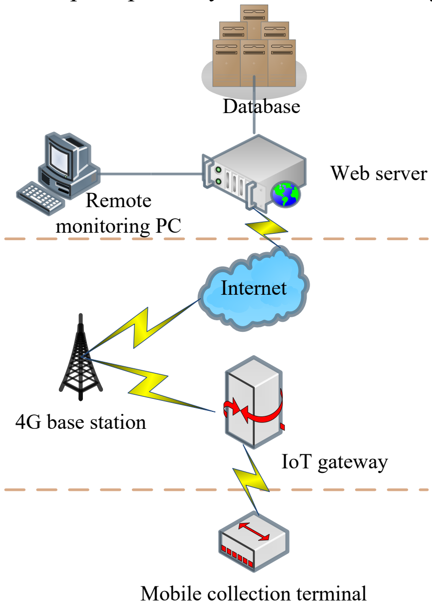

Figure 1. The overall architecture diagram of the intelligent gateway platform

In the overall architecture of the intelligent gateway platform, the vibration acquisition terminal plays the role of the perception layer, obtaining the required data by collecting vibration signals in the environment. The vibration acquisition terminal uses vibration sensors to convert vibration signals into electrical signals, which are processed and collected by data processing units. These terminals can be arranged and deployed as needed, with an indefinite number. The gateway sub platform establishes, coordinates, and maintains the entire wireless sensor network. The LoRa module serves as the main control center of the gateway sub platform, performing tasks of network management and data exchange. It communicates with the vibration acquisition terminal, receives and sends data, and transmits it to the upper layer network. 5G network is used for data transmission between the gateway sub platform and the monitoring center. The gateway sub platform establishes a connection with the remote monitoring center (monitoring server) through a 5G network and transmits the collected data to the monitoring center.

3.2. Hardware structure design

As shown in Figure 2, the hardware structure of the intelligent gateway mainly includes two parts: the gateway sub platform and the vibration acquisition terminal.

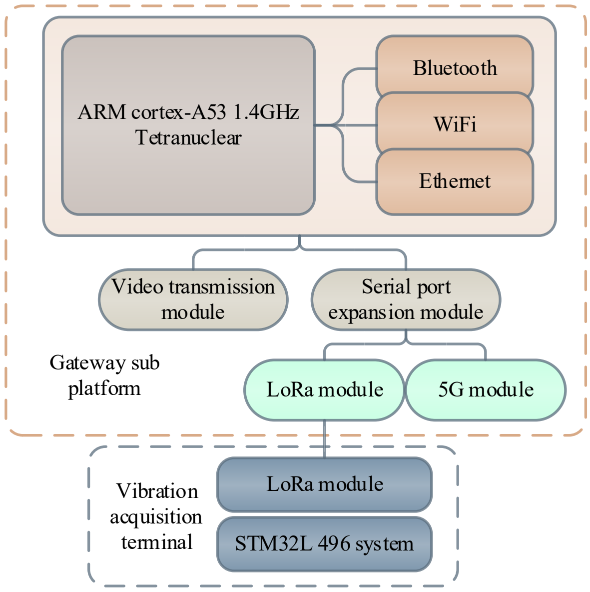

Figure 2. The overall hardware structure diagram of the intelligent gateway

The gateway sub platform is the core component of an intelligent gateway, which undertakes the tasks of data transmission and management. The main control module is the core processing unit of the gateway sub platform, responsible for controlling the operation and data processing of the entire sub platform. The communication module is used for wireless communication with the vibration acquisition terminal, and commonly used communication methods include LoRa, Wi Fi, or Bluetooth. The network management module is responsible for managing and maintaining the connection status and transmission quality of the entire wireless sensor network.

3.3. WSN node localization

In order to reduce network construction costs and improve positioning accuracy, mobile anchors are introduced to the positioning area, and the DV-HOP algorithm is used for positioning. Mobile anchor aggregation nodes and mobile anchors can achieve cost-effective communication and positioning through the introduction of multiple mobile anchors.

Each sensor node constructs its own self-organizing graph and utilizes neighboring nodes to transmit data to the aggregation node. To reduce costs, it is possible to distribute a mobile access point in each cluster, which serves as both a aggregation node and a mobile anchor. Moving an anchor can obtain its own location, and after receiving information from all nodes in the cluster, it can provide feedback on the number of hops and the shortest path, and then move to other positions in order, repeating the above communication process. The movement distance of mobile anchors cannot be too small and needs to be evenly distributed within the cluster range to ensure the coverage of nodes and the limitation of communication distance. The DV-HOP algorithm is used to determine the number of hops each moving anchor stays at multiple reference positions. The number of hops can be calculated by comparing the distance between two points, as shown in formula (1).

$$C = \frac{\sum_{j\neq i}\sqrt{(x_i-x_j)^2+(y_i-y_j)^2}}{\sum_{j\neq i}\min(h_{ik}+h_{jk})} \tag{1}$$

The transmission distance between nodes is not completely uniform, and there may be local dense and sparse phenomena. The traditional DV-HOP algorithm uses a trilateral measurement method to obtain the position of unknown sensor nodes. However, this method is sensitive to initial values and is susceptible to measurement errors, which in turn affect the final positioning accuracy. To improve positioning accuracy, it is possible to consider introducing more accurate position estimation methods, such as multilateral measurement methods or estimation methods based on probability models, to enhance positioning accuracy.

$$H_{ij} = d_{ij}/R \tag{2}$$

$$L_{ij} = \left(h_{ij} - Hi_j\right)/h_{ij} \tag{3}$$

$$\delta_{ij} = 1 - L_{ij}^2 \tag{4}$$

$$h'_{ij} = \delta_{ij} h_{ij} \tag{5}$$

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{6}$$

$$H_i = \sum_{j\neq i} \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} / \sum_{j\neq i} h_{ij} \tag{7}$$

$$O_{ij} = H_i/h'_{ij} \tag{8}$$

$$H'_i = \sum_{j\neq i} \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 h_{ij}} / \sum_{j\neq i} h_{ij}^2 \tag{9}$$

Formula (10) represents the total error between the estimated distance calculated within the communication radius and the actual distance:

$$\sum_{i\neq j} E_i^2 = \sum\left(d_{ij} - H_i \times h'_{ij}\right)^2 \tag{10}$$

Formula (11) is obtained by taking the partial derivative of Equation (10) over Ei, making the partial derivative equal to zero.

$$h'_{ij} = \sum_{j\neq i} d_{ij} H_I / \sum_{j\neq i} H_i^2 \tag{11}$$

Formula (12) was introduced to calculate the relative calculation weights W_i for the deployment positions of each mobile anchor node.

$$W_i = \left(\frac{1}{E_i^2} + \frac{1}{h_i^2}\right) / \sum_{j=1}^{n} \left(\frac{1}{E_j} + \frac{1}{h_j}\right)^2 \tag{12}$$

And formulas (13) and (14) are the final formulas used to calculate the average hop distance of each unknown node and the distance between the moving anchor position and the unknown node.

$$H_i = H'_i + \sum W_i \times E_i \tag{13}$$

$$D_{ij} = h_{ij} \times H'_i + \sum W_i \times E_i \tag{14}$$

3.4. Analysis of positioning effect

The transmission antenna, device power consumption, and remaining energy are factors that affect the communication radius of unknown and anchor nodes in NB IoT. In order to simulate the experiment, a coverage radius between 3m and 8m was selected, and the intermediate value of 5m was chosen as the number of unknown nodes, while other parameters remained unchanged.

Table 1. The influence of communication radius length on error value and average error rate

Communication radius (m)	Position error value (m)	Average error rate (%)
3	18.694	63.143
4	21.288	52.713
5	18.715	37.180
6	19.540	32.838
7	18.481	26.950
8	19.466	21.197

As shown in Table 1, when conducting distance measurement, it is necessary to balance the size of the communication radius and the variation of the average error rate. Excessive pursuit of low average error rate may lead to an increase in transmission power and energy waste, therefore a reasonable balance needs to be struck in practical applications. As shown in Table 2, it can be seen that the number of moving anchor positions has a certain impact on the average error rate.

Table 2. The influence of the number of moving anchor positions on the average error rate

Number of mobile anchor positions	Average error rate (%)
2	41.534
3	39.525
5	37.533
7	35.574
9	33.369

11	33.035
19	28.836

From Table 2, it can be seen that as the number of moving anchor positions increases, the average error rate shows a gradually decreasing trend, indicating that increasing the number of reference positions where the moving anchor stays can reduce the average error rate.

Figure 3 shows a comparison of the impact of different mobile anchor deployment methods on error rates.

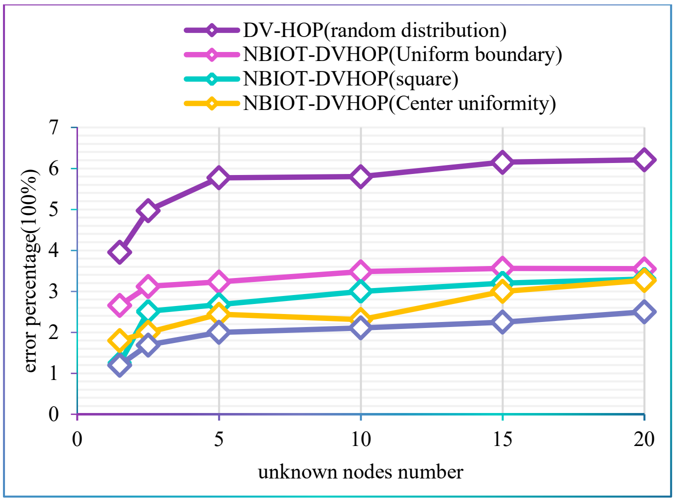

Figure 3. Comparison chart of the impact of different deployment methods of mobile anchor points on error rate

3.5. Anchor node correction

The distribution characteristics of wireless sensor network nodes are usually large-scale and randomly distributed over a large area. In order to save costs and achieve more effective positioning, it is usually chosen to evenly distribute a certain number of anchor nodes with higher costs throughout the entire monitoring area. This indicates that the node density in the local area is roughly equal to that in the entire monitoring area. According to formula (15):

$$\rho_{subarea} \approx \rho_{monitored\text{-}area} \quad (15)$$

Another strategy is to treat anchor nodes within a certain subregion as uniformly distributed, represented by formula (16):

$$\rho_A \approx \rho_B \text{ only when } Set_A \subseteq Subarea_C \text{ and } Set_B \subseteq Subarea_D \text{ and } C=D \quad (16)$$

Similarity is defined as the minimum number of hops between two nodes, where the minimum number of hops refers to the minimum number of connections required to travel from one node to another. According to this definition, formula (17) is obtained:

$$F_{sim}(hops_{ij}) \propto \frac{1}{hops_{ij}^{\ n}} \quad (17)$$

Formula (17) indicates that the similarity between two nodes is the reciprocal of the minimum number of hops plus a constant value of k. As the minimum number of hops increases, the similarity will gradually decrease. Furthermore, formula (18) is obtained:

$$\begin{aligned} & F_{sim}(hops_{ij}) = \alpha \cdot \frac{1}{(hops_{ij}+1)^n} + \beta \\ \text{s.t.} \quad & F_{sim}(0) = 100\%, F_{sim}(hops_{max}) = 0 \end{aligned} \quad (18)$$

Calculate parameters based on similarity conditions α and β, and obtain formula (19):

$$F_{sim}(hops_{ij}) = \frac{(hops_{max}+1)^n}{[(hops_{max}+1)^n - 1]} \cdot \frac{1}{(hops_{ij}+1)^n} + \frac{1}{1-(hops_{max}+1)^n} \quad (19)$$

The delay coefficient k is introduced, and based on a large number of experiments, the range of delay coefficient k values is obtained as formula (20):

$$hops_{max} \leq k \leq 2\ hops_{max} \quad (20)$$

Formula (20) indicates that the delay coefficient k ranges from 0 to 1.

When n=1, obtain formula (21):

$$F_{sim}(hops_{ij}) = \begin{cases} \frac{hops_{max} - hops_{ij}}{hops_{max}(hops_{ij}/k+1)} & hops_{ij} \leq hops_{max} \\ 0 & hops_{ij} > hops_{max} \end{cases} \quad (21)$$

Formula (21) indicates that when calculating similarity, only the nearest neighboring nodes are considered. In order to select a set of anchor nodes with similarity values close to the predicted level with unknown nodes, a threshold T is set, as shown in formula (22):

$$F_{sim}(hops_{ij}) \geq T \Rightarrow hops_{ij} \leq hops_T = \frac{hops_{max} \cdot (1-T)}{1+hops_{max} \cdot T/k} \quad (22)$$

According to Table 3, it can be seen that the key step of the DV-Hop localization algorithm is based on error vector correction under different network topology settings.

Table 3. Jump threshold under different maximum hop count and similarity thresholds

$hops_T$		$hops_{max}$ 6	7	8	9	10	11	12	13	14	15
T/%	50	2.413	2.815	3.217	3.587	4.022	4.424	4.783	5.182	5.631	5.979
	60	1.788	2.186	2.444	2.791	3.060	3.358	3.718	4.030	4.282	4.655
	70	1.319	1.547	1.765	2.007	2.201	2.419	2.679	2.900	3.083	3.342
	80	0.861	1.001	1.142	1.288	1.432	1.572	1.707	1.857	2.003	2.137
	90	0.413	0.484	0.554	0.615	0.695	0.766	0.823	0.892	0.977	1.021

After the initialization of wireless sensor networks, the received anchor node information recorded in the ANIL (Anchor Node Information List) of all unknown nodes is stored in ascending order of the minimum hop count. The anchor node selection ratio can be calculated using formula (23):

$$R_{sel} = \frac{N_{sel}}{N_{total}} \tag{23}$$

By calculating the anchor node selection ratio, understand the degree to which the selected anchor node is in the estimation of position correction. If the selection ratio is low, it may be necessary to consider increasing the number of anchor nodes or reevaluating the similarity selection method to improve the accuracy of localization.

3.6. Error correction analysis

According to the situation shown in Figure 4, when there are 24 anchor nodes and 60 unknown nodes, with a detection area edge length of 100m and a communication radius of 20m, in the case of partitioned deployment, when the node number is less than 20, due to the partitioned deployment of wireless sensor network nodes, the DV-Hop method has a very large node localization error, while the EVM-DV-Hop method has made localization correction to a certain extent. The positioning error of the FC-DV-Hop method for these nodes is similar to that of other nodes, indicating that the FC-DV-Hop method has adaptability in the distribution of node areas in wireless sensor networks and can effectively correct the position estimated by DV-Hop.

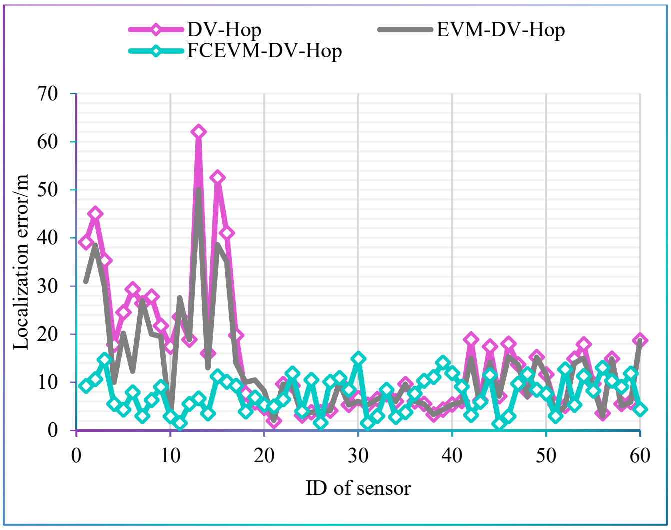

Figure 4. Comparison of positioning errors among three algorithms

When the monitoring area has a side length of 100 meters and a number of 100 nodes, different communication radii and anchor node numbers were set, and similarity thresholds were set to 0.6 and 0.7. The number of nodes participating in positioning correction was compared, and the results are shown in Table 4.

Table 4. Correction ratio of unknown nodes when similarity thresholds are 0.6 and 0.7

modification ratio/%		5	10	15	20	25	30	35	40
Similarity threshold 0.6	15	67.760	91.675	97.654	98.144	98.650	98.650	99.145	99.145
	20	55.191	88.305	98.340	98.353	99.343	99.343	98.353	98.353
	25	50.273	80.437	90.492	92.672	96.525	98.536	98.650	98.650
	30	57.621	78.484	95.373	98.732	98.353	98.353	99.739	99.739
Similarity	15	57.505	82.292	92.207	94.326	95.181	97.164	99.343	99.343

threshold 0.7	20	41.060	67.098	83.122	89.862	94.138	97.142	96.851	97.850
	25	19.142	73.545	90.672	4.957	98.732	98.732	98.155	98.155
	30	2.995	35.945	42.934	79.432	78.879	84.870	90.492	95.519

4. Network Economy Prediction and Decision Making

4.1. Economic forecasting modeling

The highly nonlinear nature of the system indicates the complex interactions and coupling relationships among various factors in the economic system, making it difficult to accurately describe and predict through simple linear models. This nonlinearity limits the use of traditional linear modeling methods. In order to better capture the complex relationships between factors, more flexible nonlinear models are needed. Using time series analysis methods, combined with external factors and trend adjustments, to more accurately predict future economic trends. Due to the fact that economic data collection and statistics are usually conducted on an annual basis, we can only use limited historical data for modeling and forecasting. This requires the introduction of appropriate smoothing techniques and data imputation methods in the model to fill in data gaps and discontinuities. At the same time, economic theory and expert knowledge can be utilized to introduce prior information and improve the predictive ability of the model. The economic system has time-varying and time-delay characteristics. In order to predict the future more accurately, data close to the prediction point should be given greater weight. This can be achieved by introducing weighted models or rolling window methods to dynamically adjust the weight and impact of data.

The method of chain data restructuring can increase the number of samples, reduce overfitting, and consider the time-varying nature of economic data time series, achieved through formula (24):

$$\left.\begin{array}{cccc} P_1 & P_2 & \cdots & P_N \\ & P_2 & \cdots & P_N \\ & & \ddots & \vdots \\ & & & P_N \end{array}\right\} V_N \tag{24}$$

Samples from different years can be assigned different weights to reflect the degree of impact of different years on the model. Through chain data restructuring, the training sample set can be expanded and more information can be used to train economic models. This helps improve the model's generalization ability, enabling it to better adapt to new data samples and predict the behavior of economic systems more accurately.

4.2. Dual Decision Information

In multi-attribute decision-making problems, the situation where experts have no preference for uncertain attribute values refers to the complexity and instability of the decision-making problem, where some attribute values are not fixed, but there are multiple possible values. Experts can only provide possible values for these attributes, and cannot accurately determine the probability distribution of each different value. In this case, it is not possible to directly use the decision matrix information provided by experts for decision-making, as the information provided by experts is incomplete.

Suppose a decision-making problem involves several attributes, such as economic indicators, market demand, etc., and experts can only provide some possible values, rather than specific numerical values. In this case, it is not possible to directly substitute these possible values into the decision matrix for calculation, as there is a lack of probability distribution information for each possible value. To solve this problem, probability allocation or other methods can be used to handle incomplete information provided by experts. The probability allocation method can estimate the probability distribution of attribute values as much as possible based on the experience and knowledge of experts and known information. Then, these probability distributions are substituted into the decision matrix for calculation and decision-making.

$$AE_l = \begin{bmatrix} e_la_{11}^1 & e_la_{11}^2 & L & e_la_{11}^{K_1} & e_la_{12}^1 & e_la_{12}^1 & L & e_la_{12}^{K_2} & L & e_la_{1n}^1 & L & e_la_{1n}^{K_n} \\ e_la_{21}^1 & e_la_{21}^2 & L & e_la_{21}^{K_1} & e_la_{22}^1 & e_la_{22}^1 & L & e_la_{22}^{K_2} & L & e_la_{2n}^1 & L & e_la_{2n}^{K_n} \\ M & M & M & M & M & M & M & M & M & M & M & M \\ e_la_{m1}^1 & e_la_{m1}^2 & L & e_la_{m1}^{K_1} & e_la_{m2}^1 & e_la_{m2}^1 & L & e_la_{m2}^{K_2} & L & e_la_{mn}^1 & L & e_la_{mn}^{K_n} \end{bmatrix} \quad (25)$$

As shown in Figure 5, Bayesian networks can help solve problems where experts are unable to provide specific attribute probability distributions. By establishing causal dependency relationships and using conditional probability tables for inference and decision analysis, they can be applied to decision-making problems in various fields, providing an effective method to solve uncertainty and decision challenges in complex environments.

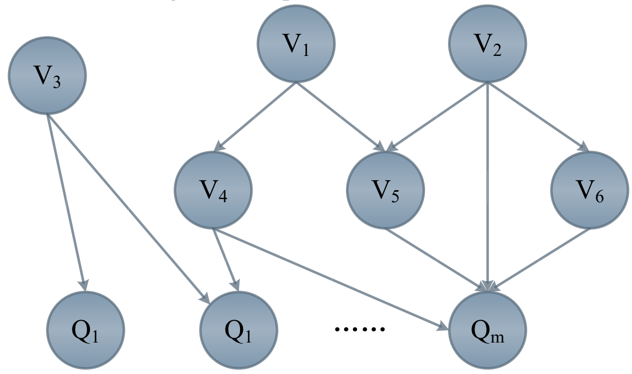

Figure 5. Bayesian network topology

Bayesian network-based reasoning can support the solution of dual information decision-making problems. By updating the probability distribution of variables in Bayesian networks through observation information, more accurate estimates of unknown variables can be obtained. For each candidate scheme, Bayesian networks can be used for inference to calculate the expected utility or economic value of each scheme under given observation information. For the ranking of advantages and disadvantages, the expected utility or value of each plan can be compared, and the plan with the maximum expected utility or economic value can be selected as the optimal plan. This way, considering known observation information and decision variables, the evaluation and ranking of plans can be based on Bayesian reasoning, and the optimal decision can be made.

4.3. Decision Model Design

According to the probability distribution derived from Bayesian networks, unknown multi-attribute decision-making problems can be transformed into risk decision-making problems. In risk decision-making problems, decision-makers can evaluate and compare the risks of different options based on probability distributions and utility functions. The decision matrix reflects the preferences and weights of experts for different attributes of the plan. By aggregating the information of all experts, methods such as weighted average can be used to calculate the comprehensive evaluation value of each scheme. In this method, the attribute values in the decision matrix are processed according to a certain standardized method in order to obtain accurate evaluation results in the subsequent calculation process. For benefit attributes, standardize using formula (26):

$$e_la_{ij}^{k'} = \frac{e_la_{ij}^k}{e_la_j^{k+}} \quad (26)$$

After this standardization process, the attribute values will be scaled between 0 and 1 according to their relative positions. For cost based attributes, standardize using formula (27):

$$e_la_{ij}^{k'} = 1 - \frac{e_la_{ij}^k}{e_la_j^{k+}} \quad (27)$$

Will:

$$p\left(a_j^k \mid p(S_i) = 1\right) \quad (28)$$

Substitute formula (28) into formula (29) for calculation.

$$S_i^{e_l} = \sum_{j=1}^{n} w_j \sum_{k\in K_j} e_la_{ij}^{k'} p_k\left(a_j^k \mid p(S_i) = 1\right) \quad (29)$$

Finally, substitute the evaluation values of the options in the decision matrices provided by each expert into formula (30) for calculation, and obtain the comprehensive evaluation value of the options:

$$S_i = \sum_{l=1}^{g} w_l^E S_i^{E_l} \quad (30)$$

By integrating the evaluation information of all experts, the final comprehensive evaluation result of the plan is obtained.

4.4. Macro control strategies

In order to further study the driving effect of various economic factors on economic growth, based on macroeconomic development control goals, the output changes of the model, especially the impact on GDP, are observed by changing the input of the model. Build a "black box" regression model to study the relationship between investment and GDP, which can be expressed using formula (31):

$$y = f(k) \tag{31}$$

By establishing a regression model, we can predict economic growth (GDP) by adjusting the value of fixed assets investment of the whole society.

4.5. Prediction and Control Effect Analysis

Table 5 compares the prediction errors of two models:

Table 5. Comparison of prediction errors between two models (%)

Year	BPANN	AI-PSO
2019	-4.282	-2.127
2020	-9.397	-3.328
2021	-12.241	-3.934
2022	-18.464	-4.045
2023	-28.976	-5.428

According to Table 5, it can be seen that the BPANN model has a larger prediction error than the AI-PSO model in all years, indicating that in this specific prediction task, the AI-PSO model performs better than the BPANN model and has more accurate prediction ability.

Table 6 shows the prediction error statistics, including the error values and error rates of two indicators.

Table 6. Prediction Error Table

Predicted time	Error value	Error rate	Error value	Error rate
2018	0.210	4.103	0.442	2.057
2019	0.181	3.239	0.367	3.258
2020	0.154	2.257	0.346	3.795
2021	0.150	1.555	0.247	4.224
2022	0.209	2.556	0.399	4.076
2023	0.217	2.023	0.350	4.282

Whether it is the total retail sales or the gross domestic product, there are certain fluctuations in the predicted error values and error rates for each year. Over time, the error rates of total retail sales and GDP forecasts have shown an increasing trend year by year.

5. Conclusion

The low-carbon energy industry plays a key role in the global response to climate change and sustainable development. As countries attach importance to emission reduction targets, investment and technological innovation continue to increase, prompting the market share of renewable energy to gradually increase. Low-carbon energy not only contributes to environmental protection, but also offers new opportunities for economic growth and energy security. Sensor technology and real-time data processing play an important supporting role in the transformation of the low-carbon energy industry. By deploying sensors, companies can monitor and analyze data on energy production, distribution, and consumption in real time to optimize operational efficiency, reduce energy consumption, and reduce emissions. Advances in real-time data processing technology have made large-scale data analysis and decision support more feasible, driving the development of intelligent energy management systems. The rise of the network economy has provided a new impetus for innovation in the low-carbon energy industry. Through the Internet platform, participants can achieve efficient information sharing and trading, which promotes the transformation of energy production and consumption patterns. For example, energy trading solutions based on blockchain technology enhance the transparency and security of transactions, creating favorable conditions for the implementation of distributed energy systems. Future research should actively explore solutions to these challenges, innovate business models, and strengthen cross-field cooperation to promote the sustainable development of the low-carbon energy industry and the deep integration of the network economy.

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