RESEARCH ARTICLE

Urban environmental data monitoring effect based on ZigBee wireless sensor network optimization model under the background of Internet of Thing

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An environmental data monitoring model was designed in response to the demand for environmental protection in various regions and to improve urban air quality by using a cost-effective ZigBee wireless sensor. Feedforward neural networks were introduced in designing prediction models for data change trends prediction to provide a basis for air protection strategies. The global search and convergence performance of the model were optimized through strategies such as batch sample training, and air quality indicators were introduced in this study. The proposed model was then validated through experiments of data detection and data prediction. The results showed that the throughput of the proposed model increased by 4.41% compared to the other models including findable, accessible, interoperable, and reusable (FAIR) model, the block chain model, the Bayesian decision classification model, and the long short-term memory network model. The prediction accuracy of the proposed model improved by 0.98% compared to that of other models, and its mean absolute error (MAE) decreased by 1.35%. The designed environmental data monitoring model had the best overall performance comparing to the other models with faster collection of environmental data and accurate data predictions, which provided reference significance for the formulation of environmental air maintenance strategies.

Keywords: ZigBee; feedforward neural network; environmental data; detection; prediction; Internet of Things.

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Introduction

When the modernization continues to accelerate, many fields such as industry and manufacturing have been rapidly developed. However, modernization also leads to increasingly serious environmental pollution. Environmental media such as air, water, and soil have all been subjected to unprecedented pollution pressure, which has seriously damaged the ecological balance and affected the health of residents [1]. The spread of fine particulate matter (PM2.5), which is the most typical pollutant, not only increases the incidence of heart disease, asthma, and other diseases, but also damages the living environment of wildlife. Therefore, the key to the construction of green cities refers to the real-time and accurate monitoring, improving, and optimizing environmental quality [2]. Environmental data (ED) detection model can collect, analyze, and predict ED through sensors. In recent years, the research on ED detection model has made remarkable progress with the rapid development of information technology, especially the wide application of the Internet of Things (IoT) and big data. Celicourt *et al*. proposed an automated ED collection technique based on findable, accessible, interoperable, and reusable (FAIR) principles. The sensor data transmission component was developed through Python, and the data was directly transmitted to the web service. The observed data model was used to store data and metadata, which reduced the manpower burden and improved the data processing efficiency [3]. Cheng *et al*. proposed a block chain-based incentive mechanism to reduce the cost of large-scale data collection. The system model included sensor layer, evaluation layer, incentive consensus layer, and ledger layer to ensure data quality. The results showed that the model effectively improved the quality of data collection [4]. Xie *et al*. developed a shallow sea ED acquisition system based on Narrowband-Internet of Things (NB-IoT). The system collected ocean data through sensors mounted on mobile buoys and uploaded data to a remote-control center using NB-IoT modules for timely analysis and visualization of the data. The results showed that this system operated stably with low power consumption and effectively monitored large area shallow sea ED, providing scientific data for marine protection and development [5]. Liu *et al*. proposed an intelligent data detection technology based on revolving door algorithm to solve the redundancy problem in large-scale data acquisition of iot sensors. The power safety terminal was automatically controlled to reduce redundant data and energy consumption through the frequency adaptive acquisition algorithm. The results showed that its application to power safety monitoring greatly improved data acquisition efficiency and system protection capability [6].

However, despite technological advancements, there are still several challenges in the study of ED detection models. The first is data quality. Due to the uneven distribution of environmental monitoring stations and the errors in the data acquisition, the model data transmission may be affected by noise and weaken the reliability of data. In addition, the complexity of the environment makes it difficult for the model to accurately predict the changing trend of environmental quality [7, 8], which requires the prediction of ED to provide data support for subsequent optimizations. Shahidehpour *et al*. proposed a machine learning classifier outage prediction model based on Bayesian decision theory for power system outage risk prediction under extreme weather. A corresponding strategy was introduced to improve the learning and training effect of the classifier considering the unbalance and sparsity of the data. The results showed that the classifier reduced outage prediction errors, thus helping operators take effective measures to improve system resilience [9]. Huang *et al*. proposed a displacement prediction model for concrete arch dam based on long short-term memory (LSTM) and two-stage attention mechanism network. The optimization strategies such as encoder-decoder architecture and attention mechanism were applied to improve the predictive performance of the model. The results showed that the method demonstrated higher accuracy and stability in the concrete dam monitoring [10]. Zheng *et al*. designed a deep learning model that combined a virtual dynamic graph convolutional neural network with a transformer model using a gated attention mechanism to accurately predict traffic flow on large-scale road networks. Further, virtual dynamic road maps were introduced to improve the complex spatial dependence of the model with a 96.77% prediction accuracy [11]. Li *et al*. proposed a predictive model based on implicit characteristics of users. The implicit relationships were discovered by K-tree algorithm. The user characteristics and network structure were represented by graph convolutional networks. The results showed that the model had the best generalization [12].

The ED detection model is of great significance for the optimization of environmental pollution and the protection of the ecological environment. Although the current technology has achieved some success, there is still a need to continuously optimize the model structure and improve the accuracy, stability, and versatility of the model. Therefore, a new ED detection model based on ZigBee wireless sensor network (WSN) was proposed in this study. The back propagation neural network (BPNN) was introduced for optimization. Batch learning and other strategies were introduced to optimize the global search accuracy and convergence performance of the model. This research would provide reference for the formulation of environmental air protection strategy.

Materials and methods

Design of environmental monitoring system based on ZigBee network and data prediction model

ZigBee has been widely used in the industrial field due to its powerful adaptive repair and other functions. It is interconnected, indicating that the transmission delay of the model can be reduced, and its effectiveness can be increased through a multi-level hop form in completing communication. This study employed the low-cost ZigBee technology commonly used in IoT to build an ED monitoring model. The study chose a mesh network topology structure for model building, which included subroutine initialization and node connection to the network. The core of the ZigBee network was the organization of coordinator nodes. Once the corresponding node was detected as a fully functional node, the node could be searched for connections to other networks. If not connected to other networks, the node could serve as the only coordinator in the model. Otherwise, the node could only exist as a child node. The connection between child nodes and the network required permission from the coordinator. The coordinator determined whether to accept the corresponding node based on its storage space and energy [13, 14]. The study then designed the coordinator and terminal modules in the ZigBee network (Figure 1).

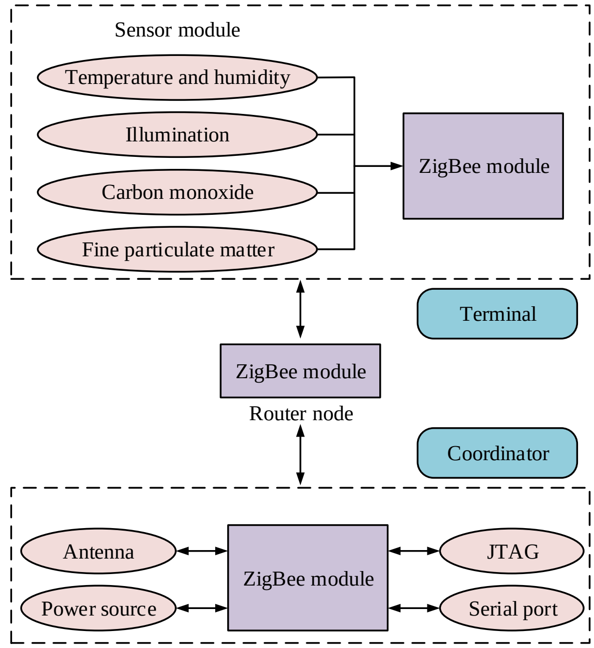


Figure 1. Structure of each module in ZigBee network.

The coordinator module needed to build and detect networks, transmit maintenance data, and obtain data quality. The CC2530 chip (Texas Instruments, Dallas, Texas, USA), a true System-on-Chip (SoC) solution for 2.4 GHz IEEE 802.15.4, ZigBee, and RF4CE applications, was used with an antenna to achieve unlimited communication over short distances. Terminal data information could be received and further displayed and processed through the upper computer program after initialization was completed. The data collection commands transmitted by the monitoring center also needed to be transmitted to the terminal through a coordinator. The terminal module was responsible for collecting and uploading ED information. The sensor module included temperature and humidity, CO, NO_2, and PM_{10}. Moreover, the normal operation relied on binding with the coordinator to ultimately achieve periodic environmental information reception. The initialization of the terminal module also included hardware and protocol stack. After successfully searching and connecting to available networks, the normal operation would enter sleep mode. After receiving the data collection command, the operation was resumed and looped through. The nodes of the entire ZigBee network were connected through wireless networks and used the ZStack communication protocol, a common implementation of the ZigBee protocol stack, with ethernet as the communication channel in the display machine. The above basic model realized real-time transmission and display of urban ED. In addition, it was necessary to predict the environmental conditions through real-time data. A relatively mature BPNN was introduced in this study to optimize the model. The basic principle was to use activation functions to transfer data through the hidden layer to the output layer. The industry-leading RF transceiver technology (Texas Instruments, Dallas, Texas, USA) was combined with extremely high reception sensitivity and anti-interference performance. The error between the expected output and the actual output was calculated to update the corresponding weight values layer by layer (Figure 2).

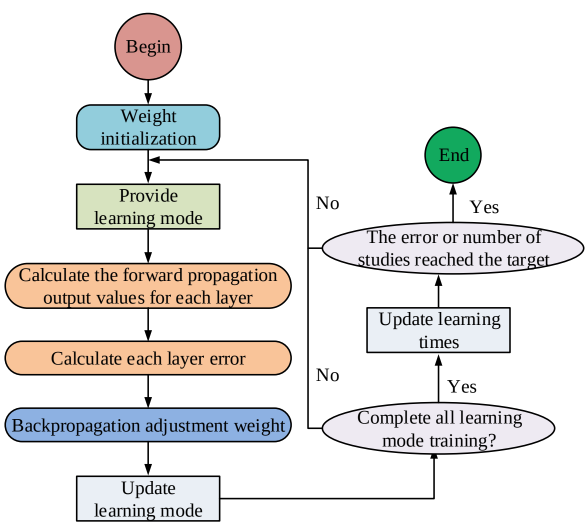


Figure 2. Operation flow of BPNN.

The initialization of weights included node connection weight v, threshold θ, error function e, and learning frequency threshold M with a value interval of (-1, 1). The outputs of each layer were calculated, and their activation function $f(x)$ was an S-shaped function. The output data were then normalized to the range of [0, 1] and expressed using formula (1).

$$f(x)=\frac{1}{1+e^{-x}} \tag{1}$$

where e^{-x} was the input signal. According to the forward propagation principle of the model, the output z_k of the hidden layer and the output y_j of the output layer nodes were represented by formula (2).

$$\begin{cases} z_k = f_1(net_k) = f_1\left(\sum_{i=1}^{a} u_{ki}x_i\right) & k=1,2,\ldots,g \\ y_j = f_2(net_j) = f_2\left(\sum_{k=0}^{g} v_{jk}z_k\right) & j=1,2,\ldots,c \end{cases} \tag{2}$$

where $i/k/j$ were to the input layer, hidden layer, and output layer, respectively. $f_1(g)/f_2(g)$ were the transfer function of the hidden layer and the everywhere layer, respectively. u_{ki} was the weight of the input and hidden layers. v_{jk} was the weight of the implicit and output layers. The weight values were then adjusted layer by layer using the error function E_p, represented by formula (3).

$$E_p=\frac{1}{2}\sum_{j=1}^{c}\left(\bar{y}_j^p - y_j^p\right)^2 \tag{3}$$

where $\bar{y}_j^p / y_j^p$ were the ideal value and the actual value, respectively. The global error E was calculated using formula (4) after updating the weights layer by layer.

$$E=\frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}\left(y_o(k)-c_o(k)\right)^2 \tag{4}$$

where m was the number of input samples. $y_o(k)/c_o(k)$ were the updated connection weight for the hidden layer and output layer, respectively. Then, new samples were randomly selected, and the above learning operations were

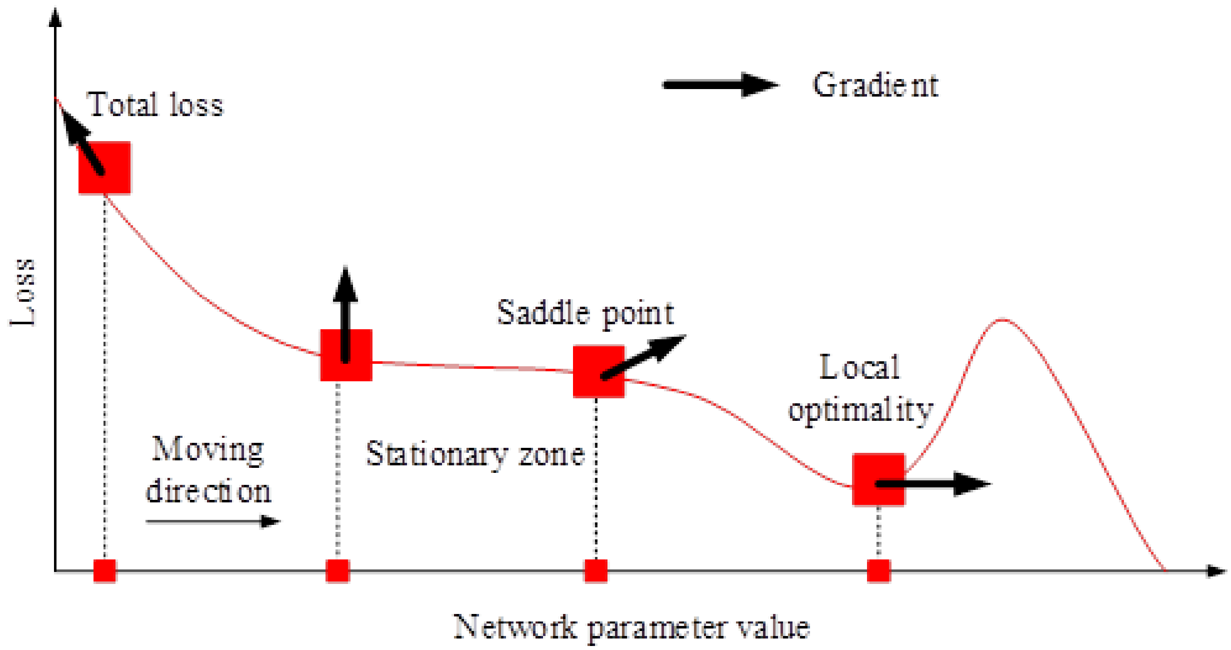


Figure 3. Schematic diagram of adding additional momentum method.

repeated.

BPNN optimization and data preprocessing module analysis

In ED monitoring, data processing was extremely important. Given the characteristics of ZigBee networks, traditional BPNN still has certain shortcomings. The local search strategy of BPNN is prone to falling into local optima when facing more complex nonlinear scenarios. The sawtooth phenomenon generated by the objective function optimization method with gradient descent can reduce the learning efficiency of the model and weaken its convergence performance. In addition, there are various issues with generalization ability and practical application feasibility. Further optimization was conducted in this study to improve the performance of the model and enhance its predictive performance. The study introduced batch processing technology that could avoid the impact of input samples on accuracy during online training and iteratively updated the network weight Δw_{ij} based on the total training error of batch samples, represented by formula (5).

$$\Delta w_{ij} = \sum V_p w_{ij} = \sum_{k=1}^{m} \delta_o(k) ho_h(k) \quad (5)$$

where $\delta_o(k)$ was the partial derivative values of each neuron in the output layer. $\delta_{ho}(k)$ were the updated connection weights of each neuron in the output layer and hidden layer. Subsequently, the study introduced a method of adding additional momentum, which added the change value of the previous weight in the update of weights and thresholds to complete feedforward adjustment through the specific calculation as follows.

$$\Delta w(k+1) = (1-m_c)\eta \nabla f(w(k)) + m_c(w(k) - w(k+1)) \quad (6)$$

where η was the learning rate. The additional momentum method was used to avoid situations where the weight value was 0, further enhancing the global optimization ability of the model. The additional momentum method was based on BPNN to add a term proportional to the changes of the previous weights and thresholds to the changes of the connection weights and thresholds of each network. Then, new network connection weights and thresholds were generated based on BPNN. This method made the network jump out of the local minimum of the error surface (Figure 3). Further, an adaptive parameter tuning technology was introduced to adjust the learning rate of the model. This method aimed to achieve adaptive adjustment of the model learning rate and minimize errors by analyzing the changes in errors, represented by formula (7) [15].

$$w(k+1) = w(k) - \eta \nabla f\left(w(k)\right) \tag{7}$$

In traditional BPNN, the sigmoid activation function is usually chosen. However, when facing larger input functions, the curve will be very smooth. The sharp decrease in slope and the reduction in gradient fluctuation ultimately lead to the problem of stagnant weight updates. Therefore, the study ignored the magnitude of partial derivatives through elastic methods and focused on the changes in their symbols. The weight change of the optimized elastic network model would decrease with the oscillation phenomenon. Meanwhile, if the direction of weight updates remained consistent, the amount of weight change would also increase. This weight update strategy could greatly improve the convergence efficiency of the model as expressed by formula (8).

$$w(k+1) = w(k) - \left(w(k) - w(k-1)\right)\sin\left(\nabla f\left(w(k)\right)\right) \tag{8}$$

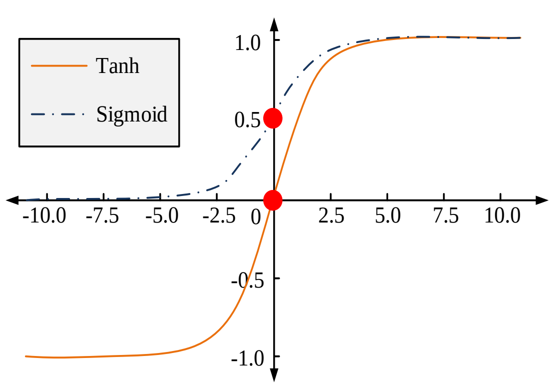


Figure 4. Comparison of change curves of different activation functions.

The study selected the Tanh activation function to replace the original activation function. The original activation function had good sensitivity only in the [-1, 1] interval. However, the sensitivity greatly decreased when the original activation function approached or exceeded the boundary infinitely (Figure 4). The Tanh function could better maintain the non-linear rise and fall effects and had good fault tolerance as expressed by formula (9).

$$f(x) = \tanh(x) = \frac{2}{1+e^{-2x}} - 1 \tag{9}$$

The study also replaced the gradient descent method with the quasi-Newton method to further enhance the convergence effect of the model, which mainly introduced the second derivative of the criterion function beyond the gradient of the search point criterion function and improved the recognition of search direction, which could contribute more effective information to the global optimal search and make the search method infinitely close to the global optimal. The specific calculation was represented by formula (10).

$$\Delta w(k+1) = w(k) - D^{-1}\nabla f\left(w(k)\right) \tag{10}$$

However, the gradient descent algorithm has a faster descent speed compared to the quasi-Newton method when the weights are small. Therefore, the study further combined them using the Levenberg-Marquardt (LM) algorithm, which not only ensured the convergence performance of the model in the early stage of search, but also enabled it to find the correct search direction when approaching the optimal point. The entire BPNN training model aimed to search for the global optimal value, while minimizing model errors. The traditional models used mean square error to represent errors. This study introduced the arithmetic means of network weights to enhance the generalization performance of the network as shown in formula (11) below [16, 17].

$$\begin{cases} F = \beta E_D + \alpha E_W \\ E_D = \frac{1}{N}\sum_{i}^{N}(t_i - y_i)^2 \\ E_W = \frac{1}{M}\sum_{i=1}^{N} w_i^2 \end{cases} \quad (11)$$

where t_i / y_i were the ideal output data and actual output data of the network model, respectively. F was the final objective function that had undergone Bayesian regularization. β / α was the objective function parameter. E_D was the mean squared error function. E_W was the sum of squared network weights. w_i was the connection weight of the network. N was the quantity of samples.

Analysis of air pollution using ED monitoring model

After completing the overall construction of the ED monitoring model, the study analyzed the air pollution index (API). According to the air quality index (AQI), environmental pollution can be divided into 6 levels. When the AQI is in the range of [0, 50], the air quality belongs to first level (excellence), and people can move freely outdoors normally. When the AQI is in the range of [51, 100], the air quality belongs to second level (good) and may have an impact on some sensitive populations. When the AQI is in the range of [101, 150], it belongs to third level (mild air pollution), and the frequency of outdoor activities should be minimized as much as possible. When the AQI is in the range of [151, 200], it belongs to fourth level (moderate air pollution). At this time, prolonged outdoor exercise may have adverse effects on patients with respiratory diseases and other conditions. When the AQI is in the range of [201, 300], it belongs to level five (severe air pollution), and the population generally produces adverse physical reactions. A larger AQI value indicates that the air quality has been severely polluted. AQI is the total sum of common air pollutants in a concentration, which constitutes the quantification of air quality as a whole. The AQI data used in this study was obtained from the real-time monitoring data of air quality monitoring stations in China (https://zx.bjmemc.com.cn/?timestamp=1718098118224), which ensured the accuracy and reliability of the data. The integrated calculation was represented by formula (12) [18].

$$IAQI_p = \frac{IAQI_{hi} - IAQI_{lo}}{BP_{hi} - BP_{lo}}\left(C_p - BP_{lo}\right) + IAQI_{lo} \quad (12)$$

where p was the type of pollutant. $IAQI_p$ was the AQI sub-index of p. C_p was the mass concentration of p. BP_{hi} / BP_{lo} were the highest and lowest limits of pollution concentration that were close to C_p, respectively. $IAQI_{hi} / IAQI_{lo}$ was the AQI corresponding to BP_{hi} / BP_{lo}. The calculation of the total AQI was as follows.

$$AQI = \max\left\{IAQI_1, IAQI_2, \ldots IAQI_n\right\} \quad (13)$$

where n was the quantity of pollutants.

The datasets used in this study included Jena Climate Dataset and the real-time air quality data collected by using Zigbee network technology and relying on the street light system of an economic development zone in Beijing, China. The Jena Climate Dataset is a time-series dataset of weather recorded at the Max Planck Institute for BioGeochemistry weather station in Jena, Germany. The dataset consisted of 14 different quantities such as air temperature, atmospheric pressure, humidity, wind direction, *etc*. that were recorded every 10 minutes. The data retrieved from this dataset was from January 1, 2009 to December 31, 2016 with a total of 420,451 pieces of data. The real-time air quality dataset contained air quality in the region from August 2022 to August 2023. After pre-processing, the datasets were divided into a test set and a training set with 60% of both datasets as training set and 40% as test set. ThinkPad E440 Ubuntu 16.04 (Lenovo, Hongkong, China) and GTX 2070

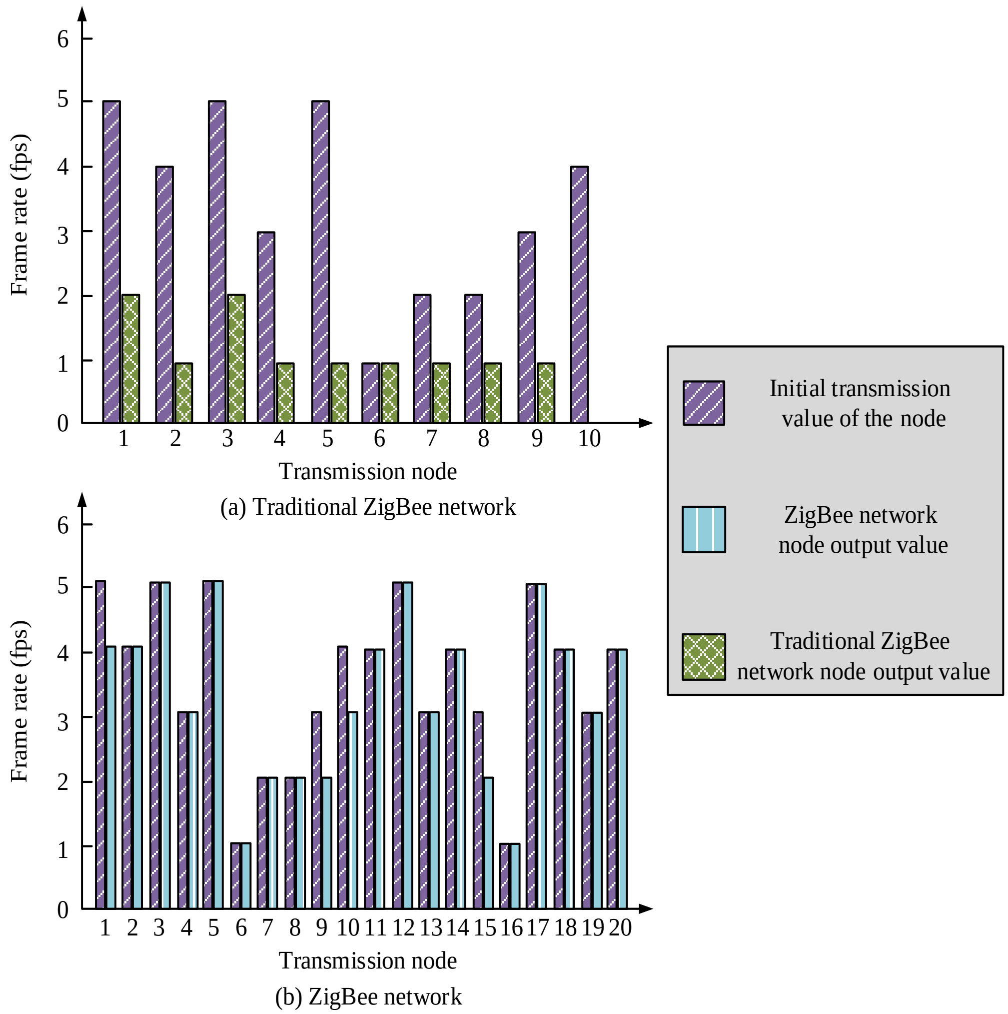


Figure 5. Comparison of data transmission performance of wireless sensor networks.

Super GPU were used in the study. TensorFlow (https://www.tensorflow.org/) and NVIDIA Jetson TX2 (Nvidia, Santa Clara, CA, USA) were used as deep learning framework and the network prediction platform, respectively. The number of input/output layer nodes was 10/1 and the number of 1/2 hidden layer nodes was 13/12. The learning rate, the number of iterations threshold, and the learning accuracy were set to 0.01, 1,000, and 0.1, respectively. To further validate the performance of the method, the FAIR model proposed by Celicourt *et al*. [3] and the Block Chain model proposed by Cheng *et al*. [4] were employed to compare the ED collection performance.

Results and discussion

Basic performance verification of ZigBee-BPNN model

The data transmission efficiency of ZigBee WSN was analyzed and verified and compared with traditional ZigBee WSN. The traditional ZigBee WSN showed poor transmission performance with complete loss of data during transmission at the 10th node and subsequent nodes. Only the 6th node achieved a 100% data transmission rate (Figure 5a). Overall, the frame loss rate of traditional ZigBee WSN reached 62.57%. The transmission performance of the designed ZigBee WSN was significantly improved with 80% of nodes achieving a data transmission rate of

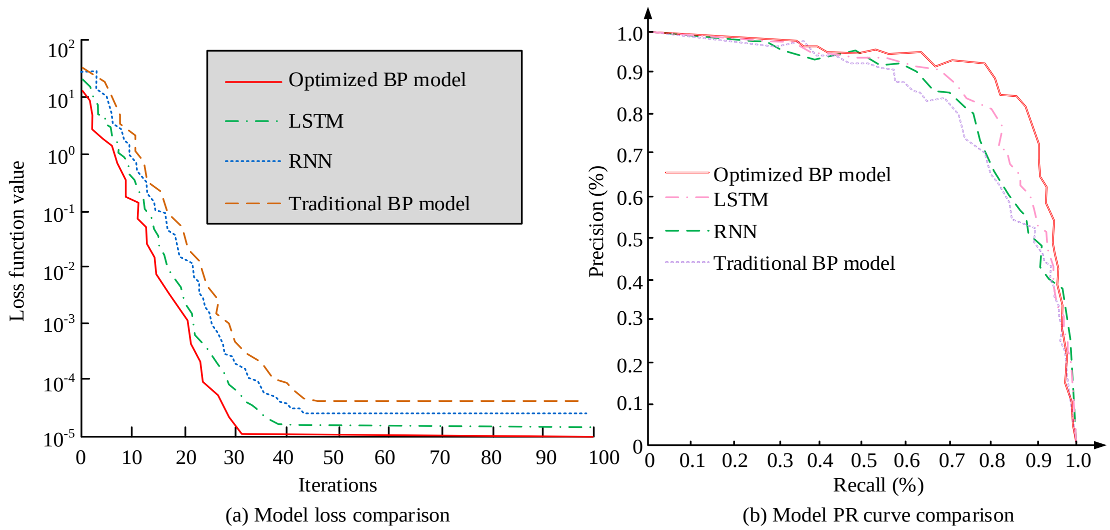


Figure 6. BPNN performance comparison.

100% (Figure 5b). Some nodes demonstrated the highest frame loss rate of only 5.06%. The average frame loss rate of the proposed model was 4.31%, which was significantly reduced by 58.26% compared to the traditional ZigBee WSN. The results indicated that the designed ZigBee WSN largely retained the original data and improved the reliability and availability of environmental monitoring data. The performance of BPNN for ED prediction was validated using the Jena Climate Dataset. The results showed that the loss value of traditional BPNN was always the highest one, while the optimized BPNN had achieved significant optimization and generally remained at the lowest level. Moreover, the optimized BPNN converged in the 30th iteration and was faster compared to other models with the average loss value of 0.001, which was a relative decrease of 5.78% (Figure 6a). The accuracy and recall of the designed BPNN were 95.41% and 96.25%, respectively. However, the accuracy and recall of traditional BPNN were 78.33% and 79.62%, respectively, which decreased by 17.08% and 16.63% compared to the optimized model. Compared with other models, the accuracy of the designed model increased by 7.91%, and the recall rate increased by 5.49% (Figure 6b). The optimized BPNN had better training performance compared to traditional BPNN and other methods.

Specific application performance of ZigBee-BPNN environmental data monitoring model

The AQI indicator data from Beijing, China in April 2022 was selected, and the predictive performance of BPNN before and after optimization was analyzed. The optimized model showed a prediction accuracy of 83.64% for CO, which was 12.29% higher than that of the traditional model (Figure 7a). The optimized model achieved an accuracy of 80.16 for predicting O_3 pollutants, which was 18.57% higher than that of the traditional model (Figure 7b). All models demonstrated good predictions for NO_2, and the optimized model achieved a prediction accuracy of 91.77%, which was 15.46% higher than that of the traditional model (Figure 7c). The predictive performances of each model on particulate matter with a diameter of 2.5 μm (PM2.5) and 10 μm (PM10) were shown in Figures 7d and 7f. The average accuracy of this optimized model reached 86.32% with an improvement of 11.98% compared to the traditional model. The prediction curves of each model for SO_2 were shown in Figure 7e. The optimized model had a prediction accuracy of 78.61%, which was an overall improvement of 9.93% compared to the preoptimized model. The

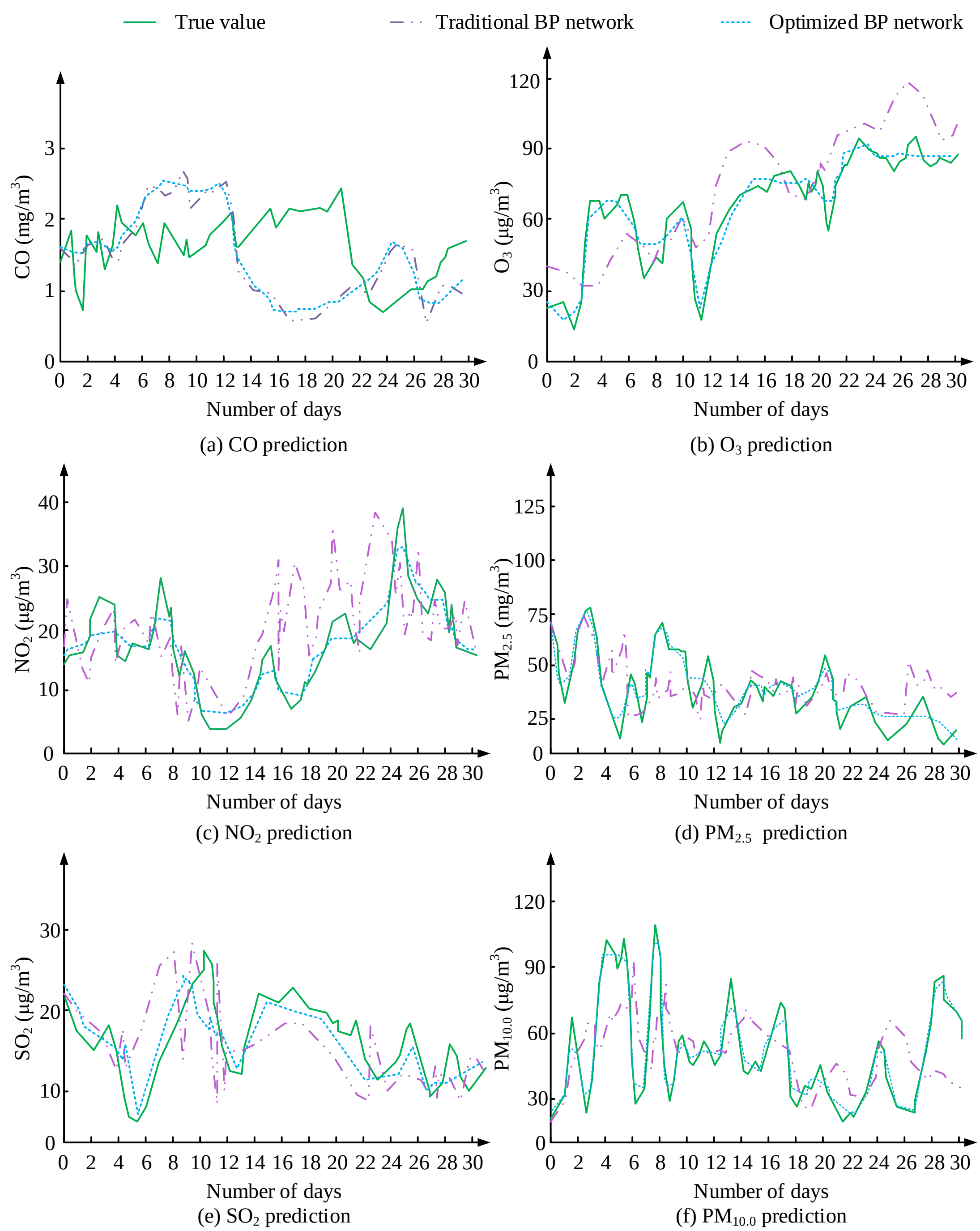
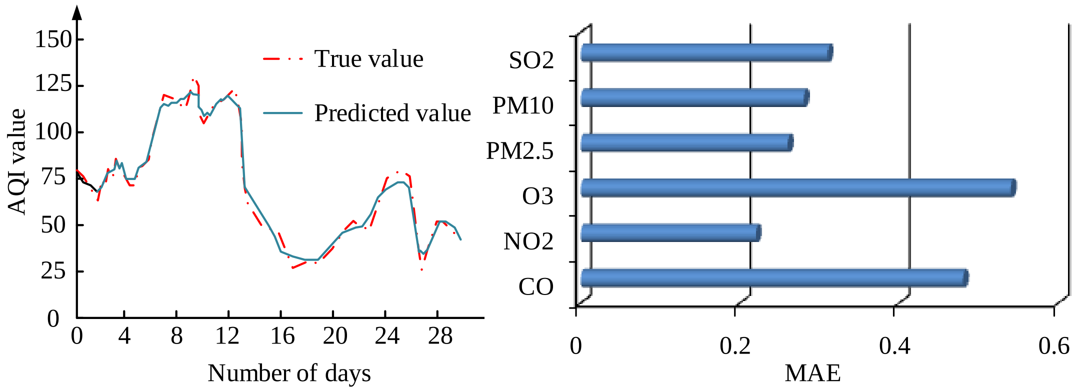


Figure 7. Comparison of BPNN prediction performance before and after optimization.

prediction accuracy of the proposed model was significantly improved with an average improvement of 11.24%. The study then analyzed the Mean Absolute Error (MAE) of each ED and the overall changes in AQI. The proposed model demonstrated the ability to accurately predict the daily air AQI with the average accuracy reaching 94.36% (Figure 8a). The results indicated that the proposed model provided certain references and significance for air quality control. The error values of the model for predicting various pollutants were shown in



(a) AQI prediction bias (b) MAE change

Figure 8. Analysis of model prediction effect.

Table 1. Comparison of environmental data detection performance of each model.

Index		**Model**		
		Proposed model	**FAIR**	**Block Chain**
Data detection	Handling capacity	8.17 bits/s	8.09 bits/s	7.45 bits/s
	Transmission delay	30.26 ms	29.98 ms	32.14 ms
Index		**Proposed model**	**BDT**	**LSTM**
Data prediction	Accuracy	94.36%	93.52%	94.19%
	MAE	0.31	0.36	0.32

Figure 8b. The predicted MAE value for NO_2 was the lowest one, only 0.22. The predicted MAE for O_3 pollutant was the highest one, reaching 0.54. The average predicted MAE of the model was only 0.31. Combining the prediction curve, except for a few nodes with significant estimation bias, the predictions of most nodes were relatively consistent with the actual situation.

The BDT classification model proposed by Mohammadian *et al*. [9] and the LSTM proposed by Huang *et al*. [10] were additionally used to compare the data prediction performances with proposed model. The results showed that the network throughput of the proposed model was relatively improved by 4.41%. The transmission delay of each model was within 35 ms with FAIR having the lowest transmission delay, a decrease of 0.93% compared to the proposed model. Compared with Block Chain, the proposed model reduced latency by 6.21%. Therefore, the proposed ZigBee network had the best overall performance in data detection. When comparing data prediction, the proposed model showed the best performance with the prediction accuracy being improved by 0.98% and the MAE value decreased by 1.35% (Table 1). The proposed model had good data detection and prediction performance.

Conclusion

An ED detection model based on ZigBee WSN was proposed based on the Internet of Things to facilitate the maintenance process of ambient air in this study. The results showed that the transmission performance of ZigBee WSN was significantly improved compared with the traditional model. There were only a small number of nodes with frame loss with a maximum loss rate of 5.06% and an average loss rate of 4.31%. The accuracy rate and recall rate of the BPNN designed in this study were 95.41% and 96.25%, respectively. Compared with the traditional BP network, the accuracy rate increased by 7.91% and the recall rate increased by 5.49%. In the specific simulation analysis, the results showed that the prediction accuracy of the proposed model for different air pollutants reached 85.49%, which was significantly improved compared with the traditional BP network with an average increase of 11.24%. The average prediction accuracy of AQI reached 94.36%. The predicted MAE value for NO_2 was the lowest, only 0.22. The MAE value of O_3 pollutant was the largest, reaching 0.54. The average predicted MAE value of the model was only 0.31. In comparison with other models, the network throughput of the proposed model was relatively improved by 4.41%. The transmission delay of the model was reduced by 6.21%. The proposed network model had better performance of data detection and prediction. However, the study only conducted on the data of a city in April 2022, and the overall data volume was small. The data collection range should be expanded in the future to further improve the accuracy of the model.

References

1. Cappa F, Franco S, Rosso F. 2022. Citizens and cities: Leveraging citizen science and big data for sustainable urban development. Bus Strateg Environ. 31(2):648-667.
2. Tang MX, Huang XF, Yao PT, Wang RH, Li ZJ, Liang CX. 2023. How much urban air quality is affected by local emissions: A unique case study from a megacity in the Pearl River Delta. Atmos Environ. 299(1):119666.
3. Celicourt P, Sam RD, Piasecki M. 2023. Rapid prototyping of an automated sensor-to-server environmental data acquisition system adopting a fair-oriented approach. J Environ Info. 41(1):1726-2135.
4. Cheng K, Quan SY, Yan JQ: A blockchain-based crowdsourcing system for large scale environmental data acquisition. In 24th IEEE International Conference on Computer Supported Cooperative Work in Design. Volume 1. 1st edition. Edited by Cheng K. China: Dalian. 2021:855-860.
5. Xie L, Xing C, Wu Y, Zhang D: Design and realization of marine Internet of Things environmental parameter acquisition system based on NB-IoT technology. In ICCBN 2021. Volume 2021. 9th edition. Edited by Xie L. China: Yunnan. 2021:257-260.
6. Liu B, Yang A, Tan X, Deng M. 2023. A frequency adaptive data collection method for internet of things nodes. J Circuit Syst Comp. 32(4):2350066-2350083.
7. Valencia VH, Levin G, Ketzel M. 2023. Densification versus urban sprawl. Modeling the impact of two urban growth scenarios on air quality. Atmos Environ. 310(1):119963-119976.
8. Kim CH, Jo HY, Jo YJ, Lee HJ, Kim JM, Lee NM, *et al*. 2023. Synoptic meteorological conditions and contributing factors to air quality during the SIJAQ campaign. Atmos Environ. 309(1):119939-119994.
9. Mohammadian M, Aminifa F, Amjady N, Shahidehpour M. 2021. Data-driven classifier for extreme outage prediction based on bayes decision theory. IEEE T Power Syst. 36(6):4906-4914.
10. Huang B, Kang F, Li J, Wang F. 2023. Displacement prediction model for high arch dams using long short-term memory based encoder-decoder with dual-stage attention considering measured dam temperature. Eng Struct. 280(3):1-15.
11. Zheng G, Chai WK, Zhang J, Katos V. 2023. VDGCNeT: A novel network-wide virtual dynamic graph convolution neural network and transformer-based traffic prediction model. Knowl-Based Syst. 275(9):110676-110682.
12. Li Q, Xie YF, Wu XH, Xiao Y. 2023. User behavior prediction model based on implicit links and multi-type rumor messages. Knowl-Based Syst. 262(1):110276-110276.
13. Yao S, Feng L, Zhao J, Zhao Q, Jiang W. 2021. PatternBee: Enabling ZigBee-to-BLE direct communication by offset resistant patterns. IEEE Wirel Commun. 28(3):130-137
14. Alagheband MR, Mashatan A. 2023. Formal unlinkability analysis of message authentication protocols based on authentic channels. J Supercomput. 79(7):8097-8123.
15. Coe RG, Manuel L, Haselsteiner AF. 2022. On limiting the influence of serial correlation in metocean data for prediction of extreme return levels and environmental contours. Ocean Eng. 266(9):113032-113043.
16. Zeng F, Wan R, Xiao Y. 2022. Predicting the self-diffusion coefficient of liquids based on backpropagation artificial neural network: A quantitative structure-property relationship study. Ind Eng Chem Res. 61(48):17697-17706.
17. Soltani-Mohammadi S, Hoseinian FS, Abbaszadeh M, Khodadadzadeh M. 2022. Grade estimation using a hybrid method of back-propagation artificial neural network and particle swarm optimization with integrated samples coordinate and local variability. Comput Geosci-Uk. 159(1):104981-104981.
18. Kassaymeh S, Al-Laham M, Al-Betar MA, Alweshah M, Abdullah S, Makhadmeh SN. 2022. Backpropagation neural network optimization and software defect estimation modelling using a hybrid salp swarm optimizer-based simulated annealing algorithm. Knowl-Based Syst. 244(3):108511-108527.