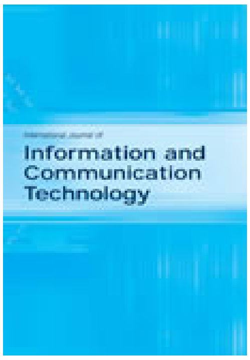

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Design of smart city environment monitoring and optimisation system based on NB-IoT technology

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Abstract: To address the issues of high network latency and large prediction error in urban environment monitoring methods, this article offers a design approach for smart urban environment monitoring and optimisation system. Firstly, the system architecture was designed to deploy the communication network using NB-IOT technology, and the edge server was utilised to perform edge computation on the trace elements of the environment as a way to obtain new locations. Then the optimal weighting algorithm is applied for optimal solution fusion, and the fused measurements are the best monitoring data. Finally, the monitoring data are input into the BP neural network improved by particle swarm optimisation (PSO) method for environmental risk prediction. Experiments indicate that the proposed method reduces the network delay by 2.86 s–13.18 s and the prediction error by 0.0236–0.0777, which not only performs real-time environmental monitoring but also maintains a low prediction error.

Keywords: environmental monitoring; NB-IOT technology; optimal weighting; particle swarm optimisation algorithm; PSO; BP neural network.

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Biographical notes: Linna Wang worked in the Beijing Polytechnic with a Master's degree. Her research interests include information and communication technology.

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1 Introduction

With the sharp increase in urban population, it will inevitably lead to more serious urban diseases, especially environmental problems: water shortage and pollution, air quality has declined sharply, solid waste pollution is on the rise, and noise pollution occurs from time to time. In all corners of our cities, there is a lot of monitoring data for various elements of the environment that are isolated and not effectively networked (Musse et al., 2018). To better serve the city and facilitate the fine management of the city, it is necessary to study and design an intelligent urban environmental monitoring system. Currently, communication technologies are developing rapidly, such as GPRS, ZigBee, LoRa, NB-IoT, etc. Among them, NB-IoT is characterised by low power consumption, low cost, wide coverage, and massive connectivity compared with other technologies (Mahbub, 2020), which can be integrated into environmental monitoring to better solve the problems of transmission and monitoring.

Environmental monitoring systems involve technologies such as computers, sensors, communications, embedded, and networks, and advances in each of these technologies have contributed to their development. Among them, the development of communication technology has revolutionised environmental monitoring technology (Martinez et al., 2019), and a wide variety of wireless communication technologies have emerged and brought about dramatic changes in environmental monitoring systems. Lv et al. (2019) designed an urban environment monitoring system relied on IEEE 802.15.4, but the network latency is high. Ye et al. (2018) designed a remote Supervising system for farmland environment relied on ZigBee and GPS, which is affected by interference. Lachtar et al. (2020) designed an environmental monitoring system for urban buildings based on LoRa wireless communication technology but the network latency was long. Chisab et al. (2023) designed an environmental monitoring system for grain silos based on nRF24L01 wireless communication technology but the transmission rate was affected by the high frequency and the latency was long.

As the internet of things (IoT) rapidly growing, the demand for hundreds of millions of monitoring terminal devices in the world every year has gradually magnified the drawbacks of the traditional wireless communication technology, which is complicated in structure, high in cost, and poor in scalability, and is difficult to support resource-constrained terminal devices (Al Mamun and Yuce, 2019). The emergence of NB-IoT technology can solve the problems of complex structure and high cost of traditional wireless communication technology. Its use of authorised network bands has received a lot of attention at home and abroad for its merits of low power expenditure, large connectivity, broad coverage, and low cost (Kadusic et al., 2022). Brdulak (2020) studied NB-IoT-based urban environmental monitoring system to realise remote monitoring of greenhouse temperature and humidity, brightness, soil pH and other parameters, which is with low power consumption and low cost, but the accuracy of monitoring is not high. Yau et al. (2022) constructed a three-dimensional urban atmospheric grid monitoring system relied on NB-IoT by effectively combining near-ground monitoring technology with ground-based remote sensing monitoring technology through atmospheric gridded micro-monitoring stations, microwave radiometers, and atmospheric particulate matter monitoring LIDAR to realise the monitoring of atmospheric pollutants. Zhang (2020) combines NB-IoT and LoRa to optimise an urban environment monitoring system with functions such as monitoring temperature, voltage, water accumulation and humidity, as well as abnormal alarms. Roosipuu et al. (2023) studied the optimisation of urban environment supervising system relied on NB-IoT, and used NB-IoT modules, various types of environmental sensors and IoT platforms to complete the optimisation design of the whole system and realise the united supervising and governance of urban environment.

Although above scholars applied NB-IoT to the environmental monitoring system, only NB-IoT modules are used as relays, which makes the network latency high. In view of the above shortcomings, this article suggests a design approach for smart city environmental monitoring and optimisation system relied on NB-IoT technology. The chief work of the method is synopsised as bellow.

1 The IoT information service architecture is briefly analysed, and the three-layer system architecture of this paper is designed with reference to this architecture, including the terminal layer, the communication network level, and the cloud platform level, and the terminal framework in the terminal layer is designed in detail.

2 NB-IOT technology is used to deploy the communication network, and edge servers are used to compute environmental trace elements, reduce data transmission delay, and divert tasks from the cloud centre. The optimal weighting algorithm is used for information fusion, searching for the optimal solution corresponding to different nodes according to the node measurements, and synchronised monitoring is achieved by the fused measurements of the optimal solution.

3 Input the monitoring data into the PSO-BP environmental risk prediction module in the cloud platform layer for prediction. Aiming at the problem that BP neural network (BPNN) can easily fall into the local optimum, particle swarm optimisation (PSO) is used to improve the updating strategy of weights and thresholds in BPNN, so as to enhance the accuracy of prediction.

4 The experimental outcome indicates that the suggested approach has a network delay of 8.35 s and a mean absolute error (MAE) of 0.0682, which is good for real-time environmental data monitoring and accurate environmental risk prediction.

2 Relevant theoretical foundations

2.1 IoT information service architecture

The IOT enables intelligent management of cities by connecting home devices, urban facilities and improves efficiency and comfort. IOT is the network of everything interconnected with a four-layer architecture down to the top as sensing level, network level, platform level, and endpoint level (Kim et al., 2018) as shown in Figure 1.

1 The sensing layer is the data foundation of the whole IoT system, which is responsible for converting the collected physical data into electrical signals that can be transmitted, and finally forwarded to the application level through the network l level and platform level.

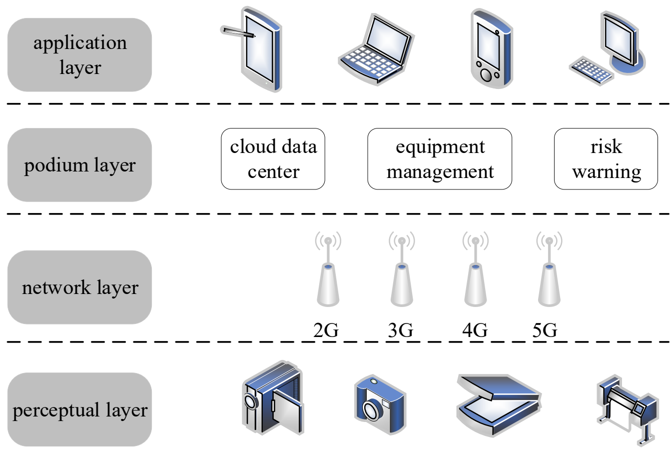
2 The network level is an essential link in the current IOT system architecture and industry chain, playing the function of data transmission, capable of uploading the data obtained from the sensing layer to the cloud server.

3 The platform layer provides a cross-platform, cross-application and cross-system unified interface for data storage, retrieval, usage, business planning, security, maintenance, billing and other functions.

4 The application layer contains a variety of intelligent application terminal devices, which can not only summarise and analyse the data uploaded from the perception

layer and present it to the customer by means of pictorial means, but also recognise the user's operation.

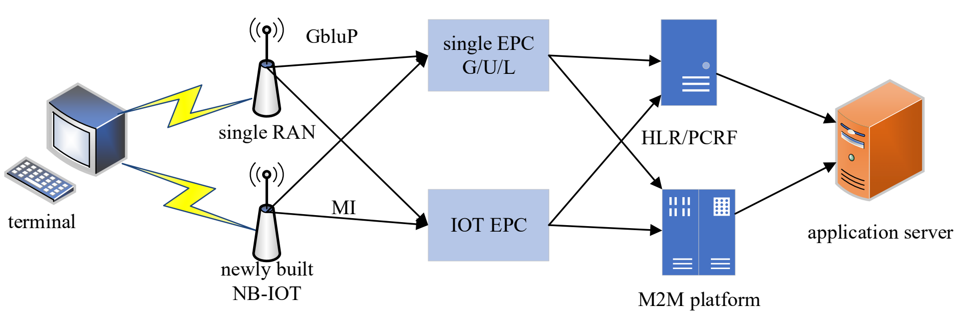
Figure 1 IoT system architecture (see online version for colours)



2.2 *NB-IOT wireless communication network technology*

NB-IoT is an IOT technology system based on mobile communication networks, its main characteristics are the large number of connectable numbers, relatively low power consumption, and large coverage area, and the emergence of this technological advantage makes up for the shortcomings of imperfect technology and small coverage area in the previous IOTs (Kanj et al., 2020), and improves the ability of the IOTs to be applied in the life. The entire network framework of NB-IoT is mainly classified into five parts, as implied in Figure 2.

Figure 2 Network framework for NB-IoT (see online version for colours)



1 Terminal: connected to the fundamental station by the air interface, the terminal side contains manufacturing terminal and NB-IOT module. The manufacturing terminal includes chips, modules, sensor interfaces, etc. The NB-IOT module includes wireless transmission interfaces, soft SIM devices, sensor interfaces, etc.

2 Wireless network side: it includes two types of network organisation, one is overall wireless access network, containing 2G/3G/4G/5G and NB-IOT wireless network. New access network undertakes operations for example air port access processing, location management, etc. and forwards non-access level data to high-level network components for processing.

3 Core network side: the network elements contain two types of network organisation, one is the integral evolutionary packet core network, and the other is the IOT core network, which supports the access of NB-IOT and eMTC users by the IOT EPC network components, as well as the EPC shared by GSM, UITRAN, and LTE.

4 IOT support platform: including attributed location register, home location register (HLR), policy control and billing rules functional unit PCRF, machine to machine (M2M) platform.

5 Server: it is the ultimate convergence point of IOT data, and carries out data processing and other operations in terms of the demand, including application server, edge server and so on.

3 Overall design of smart city environment monitoring system based on NB-IOT technology

In the IOT four-layer system architecture, the access and management of different service terminals are relatively independent, and the terminal access speed is slow, so it is tough to satisfy the rapid deployment demands for service deployment. On the other hand, with the development of technology, business applications are in the cloud, data storage and computation are in the cloud, and terminals can be easily accessed to the cloud at anytime and anywhere through smart NB-IOT (Migabo et al., 2020), so the traditional four-layer IOT information service architecture can be optimised into a three-layer architecture, i.e., the terminal level, the communication network level, and the cloud platform level. For this reason, this paper adopts NB-IOT technique according to the needs of the intelligent city and designs the entire architecture of the environmental monitoring system based on the optimised three-layer IOT service architecture, as implied in Figure 3.

The environmental monitoring system is designed to collect environmental data through sensors at the terminal layer, and the main environmental data collected are temperature, humidity, air pressure, and methane concentration in the environment. The environmental data gathered through the sensors are then transmitted to the collection terminal, which uses a microcontroller as the main control chip to carry out preliminary processing of the collected environmental data. The environmental data processed by the collection terminal is then transmitted to the system cloud platform through NB-IOT technology, so as to predict environmental risks through the risk prediction module. The acquisition terminal mainly includes microcontroller (MCU), NB-IoT communication module, GPS positioning module, data acquisition module, memory, alarm, LED indicator, LCD, and power module, etc. Its framework is indicated in Figure 4. The MCU controls all the peripheral devices, and the NB-IoT module transmits data to the microcontroller through the USART serial port. The main frequency of the monitoring terminal MCU is 120 MHz.

Figure 3 NB-IOT-based smart city environment monitoring system architecture (see online version for colours)

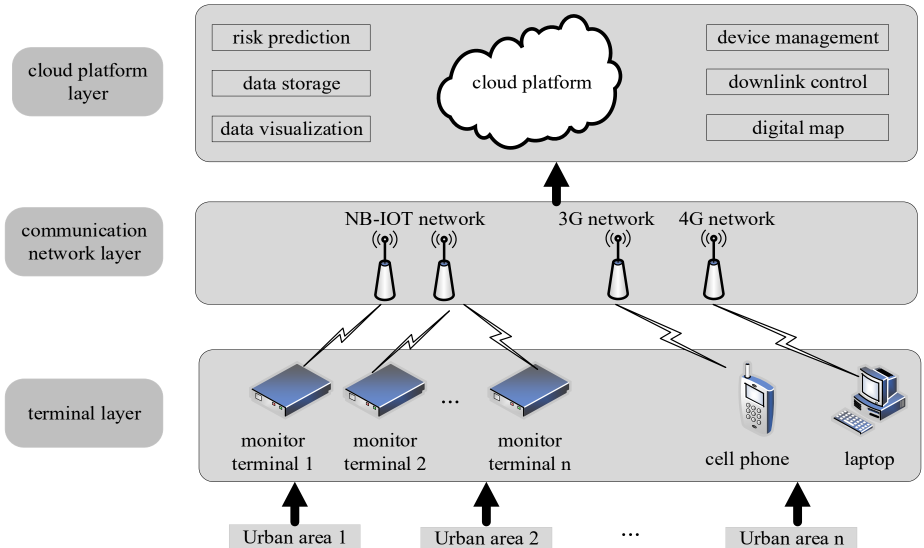
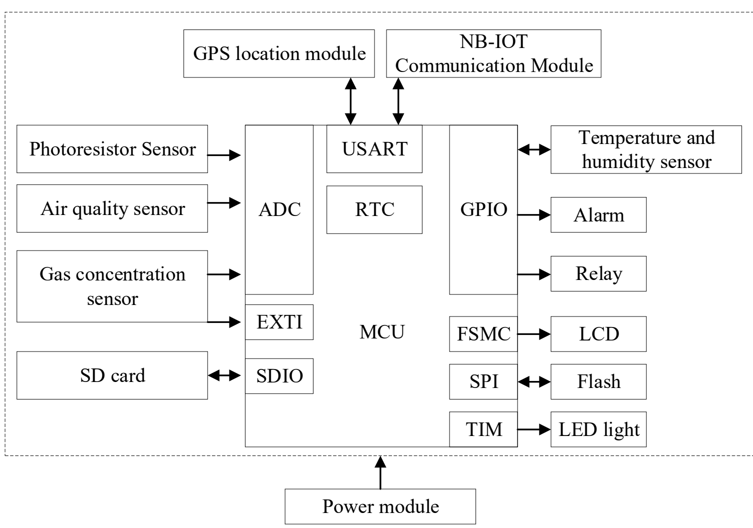


Figure 4 Monitoring terminal structure

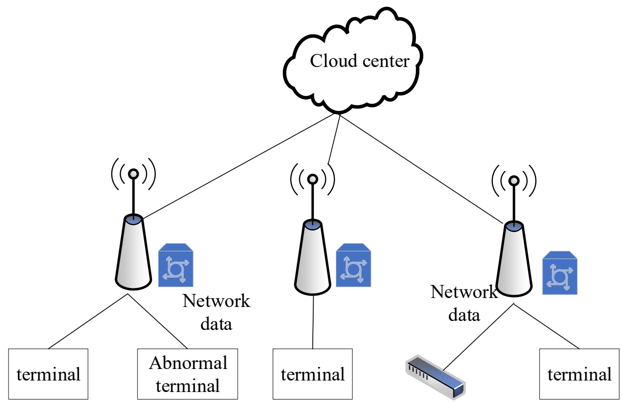


4 Design of communication network deployment and monitoring system based on NB-IOT technology

4.1 Communication network deployment based on NB-IOT technology

Relied on the overall design of the intelligent city environment monitoring system, this article utilises NB-IOT technique to deploy the communication network. In order to prevent attacks during data transmission, it is essential to detect anomalies in massive data, upload terminal device data, and use edge servers for edge computing to reduce data transmission delay and divert tasks from the cloud centre. The NB-IOT communication network deployment structure is shown in Figure 5.

Figure 5 NB-IOT communication network deployment structure (see online version for colours)



The cloud centre gets information about all edge servers and assigns different model training tasks. Set the set of edge servers to $K = \{1, 2, \ldots, k\}$ and set the transmission bandwidth between end devices and edge servers. According to the size of the training model, the amount of training samples for the isolated tree is set, and the constraint formula for defining the isolated tree is as follows.

$$\sum_{k=1}^{K} x \geqslant X_{\min} \tag{1}$$

where x is the number of isolated trees to be trained in the edge server and $X_{\min}$ is the minimum value of the number of isolated trees.

After the anomaly is detected such that the above conditions are met, an isolated tree root node is created and the dataset is populated with nodes. Subsequently, an attribute q is randomly taken in the dataset and a partition value p is randomly taken in the attribute. The data in the dataset with values less than p are placed in the left child of the current node, and the rest of the data are placed in the right child. Each leaf node contains only one sample. The formula for calculating the number of edge servers is as follows.

$$l = \left(\frac{y(y+1)}{2} - 1 \right) x \tag{2}$$

where y denotes the training samples in different isolated trees.

Repeat the recursive operation over and over again for child nodes to form new child nodes until all conditions are satisfied. Arbitrarily select two task sequences $\{x_i, y_i\}$ in the solution space of the edge server and exchange the $\{x_i, y_i\}$ sequences with them to obtain new positions. Set the height of the isolated tree and obtain the number of isolated trees of the edge server, put the obtained results into the local model and output the final set to reduce the time used for output transmission and complete the deployment of the NB-IOT communication network.

4.2 Smart city environmental monitoring based on NB-IOT technology

Due to the strong redundancy relationship between the features of different principal component variables, this paper selects the features of principal component variables based on LDA. The non-diagonal elements of the intra-class scatter matrix of the traditional LDA algorithm are the covariance between the features, which can easily lead to the model being biased towards retaining the noise features with low redundancy, so in this paper, we adopt the squared Pearson correlation coefficient to measure the feature redundancy relationship, and the specific steps are as follows.

Sensors are used for information fusion to minimise the inaccuracy of monitoring due to the influence of different sensors. After the environmental information is fused, the number of sensors is set to *N*. Each node in the cluster transmits the information to the cluster head node for the first fusion output, and the node transmits the cluster head information to the gateway. According to the measured values of the nodes, the optimal solutions corresponding to different nodes are searched according to the adaptive method, and the measured values fused by the optimal solutions are the best monitoring data. The cluster consists of *N* nodes and all nodes in the cluster monitor the target parameters from different locations. The output equation for the i^{th} node is as follows.

$$T[c] = \varepsilon_i^2 \tag{3}$$

where c is the target parameter of the sensor and ε is the weighted estimate mean square error.

Set the weighting factor of the node as a to obtain the estimated value of the weighting. Construct the auxiliary function of the weighting factor and set up a system of equations to calculate the estimated local square error of the optimal weighting factor, and obtain the minimum value results as follows.

$$\varepsilon_{\min} = \frac{1}{\sum_{i=1}^{N} \frac{1}{\varepsilon_i^2}} \tag{4}$$

where $\varepsilon_{\min}$ is the minimum value of the mean square error, N indicates the number of sensors.

The monitoring subnetwork consists of b clusters, the output of the cluster head node is c, and obeys the Gauss distribution, the inter-cluster data are processed by using the relational matrix method (Liu et al., 2012), and the confidence distances between different sensors are obtained by calculating the confidence distance measure. A smaller confidence distance result means that the outputs of the different sensors are closer together. The formula for calculating the confidence distance is as follows.

$$d = bc\left(\frac{x_j - x_i}{\sqrt{2}\varepsilon}\right) \tag{5}$$

The obtained level of trust is calculated to obtain the results of the sensor's environmental information in the network and output. According to the communication distance between nodes, the energy consumption results of different environmental signals in different directions are obtained, and the network nodes can communicate with the base station in actual time. Effectively reduce the information transmitted by the network, reduce the energy consumption of the network, improve the calculation accuracy to achieve fusion effect, and realise synchronous monitoring.

5 Cloud platform environmental risk prediction based on PSO-BP

After obtaining environmental monitoring data using NB-IOT technology, the environmental data is input to the risk prediction module in the cloud platform layer for environmental risk prediction. The risk prediction module adopts BPNN with faster training speed and stronger generalisation ability, due to the slow convergence speed and simple to fall into the local optimum of the traditional BPNN (Abdolrasol et al., 2021), the BPNN is optimised by using the advantages of PSO's fast convergence speed and global search, so as to improve the prediction effect. The specific steps are as follows.

1 Set the parameters of the PSO algorithm in the PSO-BP algorithm and initialise the population, with the position P of the particle initialised to $P_{ij}^{s+1} = P_{ij}^{s} + v_{ij}^{s+1}$ and the rate v initialised to $v_{ij}^{s+1} = \hat{u}v_{ij}^{s}$. To have better optimisation results for the weight w value in BPNN, a linearly decreasing inertia weight value is used to screen the particle dimension H as follows.

$$H = h_j + h_i \times h_j + h_j \times h_k + h_k \tag{6}$$

where h_i, h_j, and h_k are the amount of nodes in the input, implicit, and output level s, respectively.

2 When setting the BP NN parameters, the amount of nodes in the input and output layers is chosen to be 3. The amount of nodes in the hidden layer is calculated by using equation (7).

$$h_j \leq \sqrt{h_i \times (h_k + 3)} \tag{7}$$

The input to the j^{th} node of the implicit level is as follows, where θ_j is the activation function

$$I_j = \sum_{i=1}^{m} \left(w_{ij} x_i + \theta_j \right) \tag{8}$$

where w_{ij} represents the weight of the BPNN.

The output of the j^{th} node of the implicit level is $y_j = f(I_j)$. In turn, the input of the k^{th} node of the output level is calculated as follows.

$$I_k = \sum_{j=1}^{u} \left(w_{jk} y_j + \theta_k \right) \tag{9}$$

3 The MSE function of BPNN is selected as the fitness function of PSO algorithm, and the fitness values of particles are calculated as follows. The optimal position currently searched by the i^{th} particle is $p_i = (p_{i1}, p_{i2}, \ldots, p_{ij})$, and the optimal position searched by the whole particle swarm is the global extreme value, which is denoted

as $g_i = (g_{i1}, g_{i2}, \ldots, g_{ij})$. The individual optimal and global optimal are stored in p_i and g_i respectively.

$$Fitness = MSE = \sqrt{\sum_{i=1}^{M}\sum_{i=1}^{N}\left(p_{ij} - q_{ij}\right)^2 / MN} \tag{10}$$

where N is the amount of samples, M is the amount of particle dimensions, p_{ij} is the theoretical output of BPNN corresponding to sample i, and q_{ij} is the actual output of BPNN corresponding to sample i.

4 Compare the current fitness of individual particles with the fitness before iteration. If the current fitness of the particle is better than the fitness before the iteration, then the individual extreme values are updated. The velocity and position of the particle are updated by equation (11) and equation (12). The velocity of the particle is updated as follows.

$$v_{id}(t+1) = wv_{id}(t) + c_1 r_1\left(p_{id} - x_{id}(t)\right) + c_2 r_2\left(p_{gd} - x_{id}(t)\right) \tag{11}$$

where w is the inertia weight, p_{id} and p_{gd} represent different positions of the particles, c_1 and c_2 are the learning factors.

The position of the particle is updated as follows.

$$p_{id}(t+1) = p_{id}(t) + v_{id}(t+1) \tag{12}$$

where $p_{id}(t)$ is the position of the i^{th} particle at the t^{th} iteration.

5 If the current number of iterations has reached the set upper limit, or the error has reached the set minimum error, then stop the iteration before proceeding to the next step, or vice versa, go to step (4).

6 Search the optimal weights and thresholds of BPNN using PSO. Firstly, the optimisation function $Tr()$ of PSO is utilised to update the weights of BPNN, and then the learning privacy is utilised to update the threshold of BPNN.

$$w_{jk} = Tr()\left(y_k - o_k\right)o_k\left(1 - o_k\right)y_j \tag{13}$$

$$b_{jk} = c_1 b_j - \left|c_2 - c_1\right| b_j \times \left(\frac{k}{m_{\max}}\right) \tag{14}$$

where $Tr() = (p + 1)m_{\max}$, p is the number of indicators for environmental monitoring, y_k is the predicted value of the k^{th} layer, and o_k is the output of the k^{th} layer.

7 Substitute w_{jk} and b_{jk} into the BPNN and calculate the output vectors of each level of the BPNN with the network error. The output of the j^{th} neuron g_j in the implicit level is as follows:

$$g_j = g\left(\sum_{k=1}^{l} w_{jk}x_k - b_j\right) \tag{15}$$

where x_k is the input vector of the k^{th} layer and b_j represents the threshold of the j^{th} neuron. The output of the i^{th} neuron of the output level is as follows.

$$o_i = g\left(\sum_{j=1}^{m} w_{jk} g_j - b_j\right) \tag{16}$$

Then the calculated output layer node error e_k is computed, then the implied level node error e_j is computed, backpropagation is performed, and finally the overall error E is obtained from the updated weights and thresholds.

$$e_k = o_k\left(1 - o_k\right)\left(y_k - o_k\right) \tag{17}$$

$$e_j = y_k\left(1 - y_k\right)\left(\sum_{k=1}^{n} w_{jk} e_k\right) \tag{18}$$

$$E = \frac{1}{2}\sum_{k=1}^{n}\left\{y_k - f\left[\sum_{j=1}^{m}\left(w_{jk} y_k + \theta_k\right)\right]\right\}^2 \tag{19}$$

These errors are passed to the output values, and then the weights and thresholds are modified, and the errors are collected until the output is consistent with the expected results, so as to achieve the effect of monitoring and early warning of environmental risks.

6 Experimental results and analyses

To evaluate the effectiveness of the optimised urban environmental monitoring system, this paper selects a university in Shanghai as the test area of the system, and according to the characteristics of the functional zoning, the teaching building, library, laboratory building, student dormitory, student cafeteria and sports centre are divided into one type of functional areas; the commercial area near the campus is divided into two types of functional areas. An environmental monitoring point is set up at each site for long-term monitoring of the environment. China Mobile OneNET IoT cloud platform (Jabeen and Ishaq, 2023) is used for the monitoring platform, and the WH-NB73 board used for NB-IoT has embedded CoAP protocol, which can increase the low-power performance of the NB module, and the cloud platform supports the access of CoAP protocol and supports the secondary development of SDK.

For ease of analysis, the environmental monitoring system optimised in this paper is denoted as S1, the system optimised by Brdulak (2020) is denoted as S2, the system optimised by Yau et al. (2022) is denoted as S3, and the system optimised by Roosipuu et al. (2023) is denoted as S4. NB-IoT module networking delay requires re-powering up the normally operating urban environmental pollution monitoring system, at which time the system is re-started and the NB-IoT module will be re-networked. This test is carried out on the constructed environmental monitoring terminal equipment, and the time interval from the new power-up to the connection to the IoT cloud platform is displayed to show the time interval when the equipment is online. The test outcome is implied in Table 1. The networking delay of S1 is reduced by 2.86 s–13.18 s compared with S2, S3, and S4, and the networking delay of the five experiments is less than 10 s, which can satisfy the system communication quality required.

Table 1 NB-IoT module networking delay test results (s)

System	*S1*	*S2*	*S3*	*S4*
1	7.38	17.22	13.59	10.24
2	9.26	20.45	15.82	12.15
3	7.59	19.68	14.17	12.33
4	9.41	18.34	14.38	10.91
5	8.12	20.56	15.66	10.82

After NB-IoT networking, the communication delay required for the monitoring terminal to report the data through the wireless data transmission layer and for the monitoring terminal to receive the data sent from the IoT cloud platform, the communication delay of the optimised system was counted in five experiments in this paper, and the test results are shown in Figure 6. In the third experiment, the upload data delay of S1 is 6.86 s and the download data delay is 23.55 s, which is reduced by 16.69 s and 10.62 s compared to S2, 8.35 s and 8.28 s compared to S3, and 6.38 s and 0.82 s compared to S4, respectively. S1 uses the optimal weighting algorithm for information fusion, and the measured value fused by the optimal solution is the best monitoring data to realise efficient monitoring, and the test result meets the system's requirement of less than 25 s communication delay.

In addition to the comparative analysis of the performance of the system, this paper also compares and analyses the prediction performance of the designed environmental risk prediction models. S1, S2 and S4 are not designed with environmental risk prediction module, so this paper only compares and experiments with the prediction performance of S3. Correlation coefficient (R), MAE, mean absolute percentage error (MAPE), root mean squared error (RMSE) and root mean squared percentage error (RMSPE) are five commonly used indicators to measure the prediction effect, as implied in Figure 7. The various accuracy evaluation indexes of S1 are significantly better than those of S3. The MAE, MAPE, RMSE, and RMSPE of S1 were 0.0682, 0.0538, 0.0758, and 0.0739, respectively, which were reduced by 0.0236, 0.062, 0.0777, and 0.0387, respectively, compared to S3. S3 predicts environmental risks through traditional BPNN without optimising the traditional BPNN, resulting in higher prediction errors than S1. The MAE and RMSE values of the S1 model in the prediction results are lower than 0.1, which indicates that the prediction of environmental risks by PSO-BP can significantly reduce the prediction error.

Comparing the correlation coefficient R, the R-value of S1 is 0.9728, which is improved by 4.77% compared to S3, which indicates that it is effective to utilise the PSO's optimisation-seeking trajectory function to enhance the convergence speed of the BPNN. S1, which introduces inertia terms for both forward and backward transmission, outperforms the comparison model and provides a better fit for environmental risk prediction. Therefore, S1 has a better fitting effect and prediction accuracy due to the optimisation of the environmental monitoring system through NB-IOT technology, which reduces the complexity of the input data and optimises the weight update algorithm of the BPNN.

Figure 6 Monitoring terminal and IOT cloud platform communication delay test results (see online version for colours)

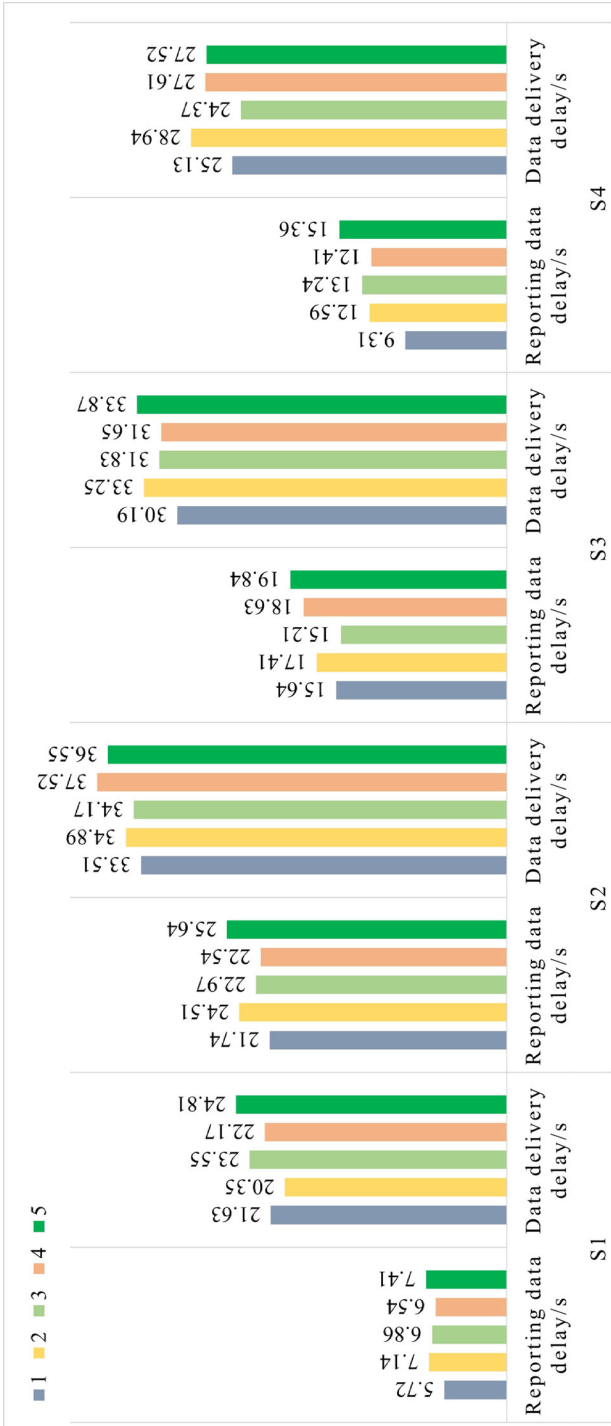
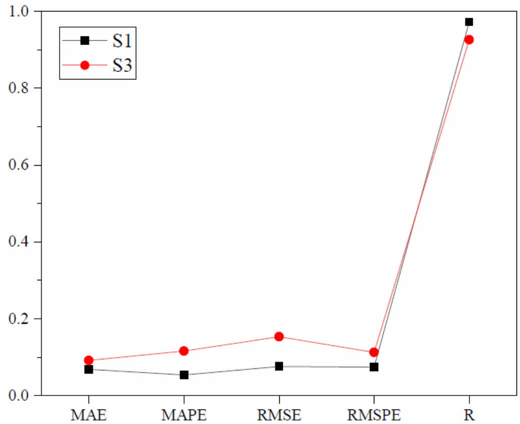


Figure 7 Comparison of predictive performance of urban environmental monitoring systems (see online version for colours)



7 Conclusions

Focusing on the issues of high network latency and low monitoring accuracy of urban environmental monitoring methods, the research on the design method of smart urban environmental monitoring and optimisation system based on NB-IOT technology was carried out. Firstly, the system architecture based on NB-IOT is designed on the basis of IOT information service architecture, and then edge servers are utilised to perform edge computation on the trace elements of the environment as a way of obtaining new locations. The optimal weighting algorithm is used for information fusion, and the measured values fused by the optimal solution are the best monitoring data to realise synchronous monitoring. Finally, the monitoring data are input to the cloud platform layer, and PSO-BP is used as a prediction method for environmental risk prediction. The experimental outcome indicates that the suggested method has low network delay and prediction error, which provides a guarantee for the monitoring and management of urban environment by relevant departments. However, the proposed method still has some optimisable space, for example, it does not take into account the power consumption of the system as a whole, which leads to the possibility of non-essential power consumption problems in the system, and thus further improvements can be made in the next step of the research.

References

Abdolrasol, M.G., Hussain, S.S., Ustun, T.S. et al. (2021) 'Artificial neural networks based optimization techniques: a review', *Electronics*, Vol. 10, No. 21, p.2689.

Al Mamun, M.A. and Yuce, M.R. (2019) 'Sensors and systems for wearable environmental monitoring toward IoT-enabled applications: a review', *IEEE Sensors Journal*, Vol. 19, No. 18, pp.7771–7788.

Brdulak, A. (2020) 'Characteristics of narrowband IoT (NB-IoT) technology that supports smart city management, based on the chosen use cases from the environment area', *Journal of Decision Systems*, Vol. 29, No. sup1, pp.489–496.

Chisab, R.F., Majeed, A.A. and Hamid, H.S. (2023) 'IoT-based smart wireless communication system for electronic monitoring of environmental parameters with a data-logger', *International Journal of Electrical and Electronic Engineering & Telecommunications*, Vol. 12, No. 6, pp.450–458.

Jabeen, M. and Ishaq, K. (2023) 'Internet of things in telecommunications: a technological perspective', *Journal of Information Technology Teaching Cases*, Vol. 13, No. 1, pp.39–49.

Kadusic, E., Zivic, N., Ruland, C. et al. (2022) 'A smart parking solution by integrating NB-IoT radio communication technology into the core IoT platform', *Future Internet*, Vol. 14, No. 8, p.219.

Kanj, M., Savaux, V. and Le Guen, M. (2020) 'A tutorial on NB-IoT physical layer design', *IEEE Communications Surveys & Tutorials*, Vol. 22, No. 4, pp.2408–2446.

Kim, J., Jeon, Y. and Kim, H. (2018) 'The intelligent IoT common service platform architecture and service implementation', *The Journal of Supercomputing*, Vol. 74, pp.4242–4260.

Lachtar, A., Val, T. and Kachouri, A. (2020) 'Elderly monitoring system in a smart city environment using LoRa and MQTT', *IET Wireless Sensor Systems*, Vol. 10, No. 2, pp.70–77.

Liu, X., Zhu, X-H., Qiu, P. et al. (2012) 'A correlation-matrix-based hierarchical clustering method for functional connectivity analysis', *Journal of Neuroscience Methods*, Vol. 211, No. 1, pp.94–102.

Lv, Z., Hu, B. and Lv, H. (2019) 'Infrastructure monitoring and operation for smart cities based on IoT system', *IEEE Transactions on Industrial Informatics*, Vol. 16, No. 3, pp.1957–1962.

Mahbub, M. (2020) 'NB-IoT: applications and future prospects in perspective of Bangladesh', *International Journal of Information Technol*ogy, Vol. 12, No. 4, pp.1183–1193.

Martinez, B., Adelantado, F., Bartoli, A. et al. (2019) 'Exploring the performance boundaries of NB-IoT', *IEEE Internet of Things Journal*, Vol. 6, No. 3, pp.5702–5712.

Migabo, E.M., Djouani, K.D. and Kurien, A.M. (2020) 'The narrowband internet of things (NB-IoT) resources management performance state of art, challenges, and opportunities', *IEEE Access*, Vol. 8, pp.97658–97675.

Musse, M.A., Barona, D.A. and Rodriguez, L.M.S. (2018) 'Urban environmental quality assessment using remote sensing and census data', *International Journal of Applied Earth Observation and Geoinformation*, Vol. 71, pp.95–108.

Roosipuu, P., Annus, I., Kuusik, A. et al. (2023) 'Monitoring and control of smart urban drainage systems using NB-IoT cellular sensor networks', *Water Science & Technology*, Vol. 88, No. 2, pp.339–354.

Yau, C-W., Jewsakul, S., Luk, M-H. et al. (2022) 'NB-IoT coverage and sensor node connectivity in dense urban environments: an empirical study', *ACM Transactions on Sensor Networks (TOSN)*, Vol. 18, No. 3, pp.1–36.

Ye, Y., Sun, X., Liu, M. et al. (2018) 'The remote farmland environment monitoring system based on ZigBee sensor network', *International Journal of Computational Science and Engineering*, Vol. 17, No. 1, pp.25–33.

Zhang, X. (2020) 'Application of NB-IoT technology in urban lighting system', *International Core Journal of Engineering*, Vol. 6, No. 4, pp.246–251.