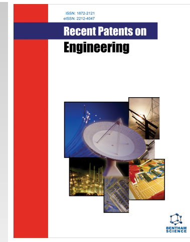
RESEARCH ARTICLE

Optimization Analysis of Urban and Rural Environmental Planning Based on Artificial Intelligence and Intelligent Information Processing Algorithms



Feng Zhao[1] and Chuanlong Han[1,*]

[1]*School of Management, Suzhou University, Suzhou 234000, Anhui, China*

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Abstract: ***Introduction***: With rapid economic development and urbanization, urban and rural areas face environmental challenges. Traditional optimization methods struggle with complexity and often fail to find global optima.

Method: This study integrates a Bidirectional Long Short-Term Memory Network (BiLSTM) with Genetic Algorithm (GA)-Ant Colony Optimization (ACO) to improve environmental planning. BiLSTM captures long-term data correlations and predicts future trends, achieving an average Mean Squared Error (MSE) of 0.0217. GA-ACO, using GA-generated solutions as initial input for ACO, identifies optimal planning solutions.

Results: This approach enhances air quality indicators and provides robust predictions and optimizations for sustainable urban and rural development.

Conclusion: To sum up, future development needs comprehensive technical progress, policy support and public participation to form a multi-level and multi-field collaborative mechanism to achieve the real sustainable development goal.

Keywords: Urban and rural environment, planning optimization, bidirectional long short-term memory network, genetic algorithm, ant colony optimization.

1. INTRODUCTION

With the acceleration of urbanization and continuous population growth, urban and rural environmental problems have become increasingly prominent, becoming one of the important factors affecting the sustainable development of the country [1, 2]. The gap between urban and rural areas not only shows significant differences in economic development levels but also shows significant imbalances in environmental quality, resource utilization, and social services. Traditional urban and rural planning [3, 4] often relies on experience and expert judgment, making it difficult to fully consider the complexity and diversity of the urban and rural environment, resulting in poor implementation of planning schemes and difficulty in achieving overall environmental optimization. It is feasible to evaluate urban and rural environmental data more thoroughly, investigate the patterns hidden in the data, and create more precise and scientific urban and rural planning models by merging artificial intelligence technology [5, 6] with optimization algorithms. This has important practical significance for promoting urban and rural environmental optimization and promoting urban-rural integration development.

The main contribution of this study is to combine the bidirectional long short-term memory network with the genetic algorithm-ant colony optimization algorithm to propose a new optimization method for urban and rural environmental planning. This method aims to address the limitations of traditional optimization methods in dealing with complex environmental problems. Traditional linear programming and dynamic programming methods often fail to find the global optimal solution when dealing with urban and rural environmental problems due to the complexity of their algorithms and the limitations of local optimal solutions. By introducing the BiLSTM model, this study effectively captures the long-term correlation of environmental data and provides accurate predictions of future environmental quality changes. BiLSTM can consider past and future information, overcome the shortcomings of traditional LSTM and GRU in dealing with long-term dependencies, and thus show superior performance in environmental quality prediction.

In terms of optimization, this study combines GA with ACO so that the solution generated by GA becomes the ini-

* Address correspondence to this author at the School of Management, Suzhou University, Suzhou 234000, Anhui, China;
E-mail: 424437665@qq.com

tial information of ACO, thereby improving the optimization effect of environmental planning. The GA-ACO method can more effectively explore and optimize environmental planning schemes by comprehensively utilizing the advantages of genetic algorithms and ant colony algorithms. The results show that compared with using GA or ACO alone, GA-ACO shows the best effect in optimizing air quality, drinking water quality, and soil quality. Especially when dealing with complex environmental data and planning problems, GA-ACO provides an effective optimization approach to improve environmental quality while promoting sustainable development in cities and rural areas.

The innovation of this study is to apply the combination of BiLSTM and GA-ACO algorithms to the optimization of urban and rural environmental planning. First, as an advanced time series prediction model, BiLSTM has the advantage of bidirectional propagation and can more comprehensively capture the temporal dependencies in environmental data. This bidirectional structure enables BiLSTM to use past and future information to make more accurate predictions of long-term trends, thereby improving the accuracy of environmental quality predictions. This innovative application breaks through the limitations of traditional models and provides new ideas and methods for environmental data analysis and prediction. Combining GA with ACO to optimize environmental planning is another important innovation of this study. GA generates potential high-quality solutions through genetic operations, and ACO uses these solutions for local search to find better planning solutions. This hybrid optimization strategy not only improves the global search capability of the algorithm, but also effectively reduces the convergence time of the algorithm. Although the convergence time of GA-ACO is slightly longer than that of GA alone, the optimization effect is significantly better.

This article comprehensively applies bidirectional LSTM and GA-ACO algorithms to optimize urban and rural environmental planning and uses bidirectional LSTM to analyze and predict urban and rural environmental data. It combines GA and ACO algorithms to optimize and solve urban and rural environmental planning problems, ultimately achieving comprehensive optimization of urban and rural environmental planning. It is possible to clean and normalize the collected environmental quality data. Trained bidirectional LSTM can be used to analyze and predict urban and rural environmental data and predict future trends in environmental quality changes.

2. RELATED WORK

Urban and rural environmental planning can optimize the spatial structure of urban and rural areas, allocate resources and factors reasonably, promote the organic flow of resources, industries, population and other factors between urban and rural areas, promote coordinated development of urban and rural economies, and narrow the urban-rural gap. Urban and rural environmental planning [7, 8] can scientifically protect and utilize ecological resources, reasonably develop and utilize land and water resources, preserve the integrity and stability of natural ecosystems, reduce environmental pollution and ecological damage, and ensure harmonious coexistence between humans and nature. Urban and rural environmental planning [9, 10] focuses on long-term development, guided by the concept of sustainable development, and unifies economic, social, and environmental interests. It promotes resource conservation and recycling, promotes coordinated development between economic development and environmental protection, and achieves sustainable economic and social development. Wang Zhao-lin [11] used an ant colony algorithm to optimize the spatial pattern evolution of rural settlements in the study area, showing a trend of concentration and close evolution. The results show that 69.1% of rural residential patches are concentrated in suitable and relatively suitable areas, with a concentration occurring near convenient transportation, complete public facilities, convenient production, and central villages. To evaluate the changes in scale from rural to urban areas over the past 20 years, Degerli, Burcu [12] conducted animal statistical analysis by distinguishing cities and rural areas located on the coastline. From 2000 to 2020, the green space area in the study area decreased by 14.1%. The optimization of urban and rural environmental planning [13, 14] can promote the integrated development of urban and rural areas and achieve the orderly flow and complementarity of resources, industries, population and other factors between urban and rural areas. By reasonably planning the layout, functional zoning, and transportation network of urban and rural areas, it can achieve interconnectivity between urban and rural areas, promote optimal resource allocation, and promote coordinated economic and social development between urban and rural areas. Analyzing urban and rural environmental planning problems through ant colony optimization algorithms can promote resource optimization allocation, but there is a lack of using artificial intelligence technology to achieve automated analysis and pattern recognition of urban and rural environmental data.

Artificial intelligence technology can analyze and predict a large amount of data, learn the trends and laws of environmental changes from historical data, predict future environmental conditions, population changes, resource utilization, *etc.,* and provide the scientific basis for planning. Artificial intelligence technology [15, 16] can combine sensor networks and the Internet of Things technology to achieve real--time monitoring and adjustment of urban and rural environments. By monitoring indicators such as environmental quality, traffic conditions, and population density, problems can be identified in a timely manner and corresponding planning and adjustment measures can be taken to improve the adaptability and sustainability of urban and rural environments. Artificial intelligence technology [17, 18] can be used to evaluate the environmental impact of urban and rural planning schemes. By simulating and analyzing the implementation effects of different planning schemes, the impact on air quality, water resources, ecosystems, and other aspects can be predicted, helping planners develop more environmentally friendly and sustainable planning schemes. By utilizing artificial intelligence technology [19], intelligent management and recycling of urban and rural resources can be achieved, which can reduce resource consumption and environmental pollution. Ma, Shijun [20] applied artificial neural network methods to estimate urban solid waste in China. From 1990 to 2017, organic components, paper, and plastic showed an increasing trend, while ash and stone significantly decreased. By combining artificial intelligence and other technologies, automated analysis and pattern recognition of urban and rural environmental data can be achieved. However, the above research lacks a comprehensive application of artificial intelligence and intelligent information processing algorithms for optimizing urban and rural environmental planning analysis.

3. METHODS FOR OPTIMIZING URBAN AND RURAL ENVIRONMENTAL PLANNING

3.1. Collect Data Related to Urban and Rural Environments

The selected area is a city in China, and the collection period is from 2000 to 2020. The collected data on urban environmental quality is shown in Table **1**.

With the increasing awareness of environmental protection and the continuous improvement of relevant regulations, the air quality in cities is gradually improving.

Due to factors such as industrial production, transportation, and population density, urban air often contains a large amount of particulate matter, harmful gases, and volatile organic compounds. Activities such as automobile exhaust, factory emissions, and construction can lead to a decrease in urban air quality and the formation of haze weather. In contrast, rural areas usually do not have as dense transportation and industrial activities as cities, and the air quality is relatively better. However, in some rural areas, the use of pesticides, fertilizers, and animal husbandry activities can also lead to a certain degree of pollution in the air in rural areas.

Urban and rural environmental analysis can provide a scientific basis for urban and rural planning decisions. By analyzing environmental quality, resource utilization, and other aspects, reasonable planning and policies can be formulated for the development of urban and rural areas, promoting coordinated development of economy, society, and environment. Urban and rural environmental analysis helps to promote the integrated development of urban and rural areas, and achieve coordinated development of urban and rural economy, society, and environment.

To ensure the quality and availability of data, preprocessing can be performed on collected data, which includes data cleaning and normalization [21, 22]. Missing value handling, outlier handling, and duplicate value handling can be performed on the collected data.

Table 1. Partial urban environmental quality data.

Years	PM2.5 Concentration (μg/m^3)	PM10 Concentration (μg/m^3)	SO_2 Concentration (μg/m^3)	CO Concentration (mg/m^3)	O_3 Concentration (μg/m^3)	NO_2 Concentration (μg/m^3)
2000	80.7	100.2	51.0	1.6	80.8	60.7
2001	82.6	98.4	48.9	1.9	82.1	62.2
2002	85.7	95.8	45.5	2.1	85.1	65.8
2003	83.7	96.4	46.7	1.9	83.8	63.1
2004	81.9	98.1	47.3	2.9	81.5	61.0
2005	79.2	99.4	48.4	2.9	79.3	59.7
2006	77.1	96.9	49.2	2.7	77.6	57.0
2007	75.2	94.2	50.9	2.4	75.8	55.1
2008	73.7	93.1	51.7	2.7	73.2	53.5
2009	71.5	94.9	52.7	2.9	71.2	51.6
2010	70.0	95.4	53.8	3.4	69.5	49.1
2011	67.1	92.3	54.8	3.1	67.8	47.7
2012	65.2	91.3	55.2	3.3	65.1	45.4
2013	63.6	90.2	56.1	3.6	63.9	43.2
2014	61.1	89.6	57.3	3.0	61.5	41.9
2015	59.2	87.4	58.8	3.3	59.2	39.1
2016	58.0	88.2	59.9	3.5	57.6	37.9
2017	55.1	85.1	60.5	3.3	55.8	35.2
2018	53.3	85.5	61.6	4.0	53.5	33.1
2019	51.6	84.9	62.3	3.8	51.4	31.6
2020	49.6	83.9	63.9	4.3	49.8	29.3

For missing and outliers, the mean of the data is used to fill in and replace them. The formula for calculating the mean of the data is:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

The dataset can be checked for duplicate data, detecting completely duplicate rows or samples, deleting duplicate data, and retaining only one piece of data information.

In the collected data, the range and units of values for different features may vary, which can lead to significant differences between different features. Data normalization can eliminate the dimensional influence between different features, making each feature within the same dimensional range, which is beneficial for improving the stability and convergence speed of the model. The normalized formula is represented as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2}$$

3.2. Establishing a Bidirectional LSTM Model

With the acceleration of urbanization and the improvement of industrialization, urban and rural environmental problems are becoming increasingly prominent, such as air pollution, water pollution, soil pollution, *etc.* By predicting and analyzing urban and rural environmental data, it can identify the changing trends and potential risks of environmental problems in advance, providing a scientific basis for environmental protection and governance. By predicting and analyzing urban and rural environmental data, timely discovering changes in environmental quality is beneficial for early warning of environmental risks and ensuring the health and safety of residents.

The bidirectional long short-term memory network is an improved LSTM structure that runs two independent LSTMs simultaneously on the input sequence of each time step [23, 24]: one reads the sequence from front to back, and the other reads the sequence from back to front.

The model structure of bidirectional LSTM is shown in Fig. (**1**).

At each time step, the backward LSTM receives the input at the current moment and the hidden state at the next moment and outputs the output at the current moment and a new hidden state.

The output of bidirectional LSTM is a concatenation of forward LSTM and backward LSTM outputs, which can capture the contextual information of the current time step at each time step. For each time step t, the output of bidirectional LSTM is a connection between forward and backward outputs:

$$Output_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \tag{3}$$

Introducing nonlinearity through activation functions to solve the problem of linear inseparability. The formula for the sigmoid function is expressed as:

$$S = \frac{1}{1+e^{-x}} \tag{4}$$

During the training process, bidirectional LSTM can backpropagate errors based on the loss function and update model parameters through optimization algorithms such as gradient descent to better fit the training data. The loss function formula is:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{5}$$

The update rule for gradient descent is:

$$\theta_{t+1} = \theta_t - \alpha \cdot \nabla L(\theta_t) \tag{6}$$

In formula 6, θ_t represents the result of the t-th iteration of the model parameters, α is the learning rate, and $\nabla L(\theta_t)$ is the rate of change of the loss function at the current parameter point. Trained bidirectional LSTM can be used to analyze and predict urban and rural environmental data and predict future trends in environmental quality changes.

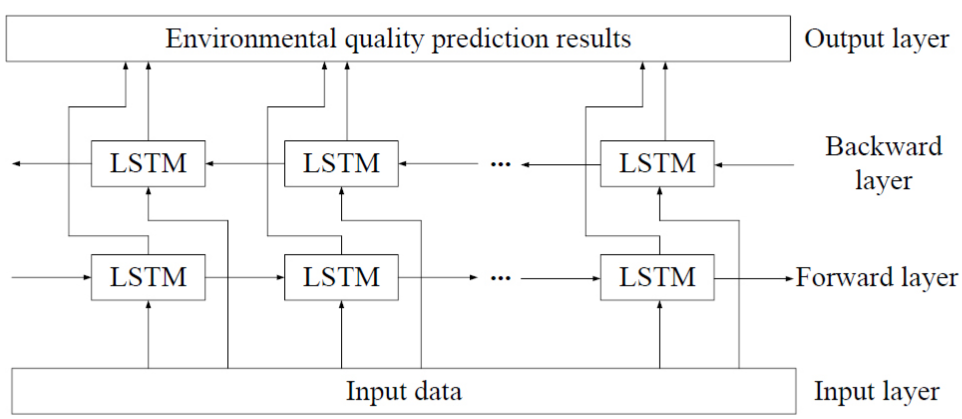

Fig. (1). Bidirectional LSTM model.

3.3. GA-ACO Algorithm Design

With the acceleration of population mobility and urbanization, the imbalance of urban-rural development and the pressure on resources and the environment are becoming increasingly prominent. It is necessary to solve the problems of development differences and uneven resource allocation between urban and rural areas through planning optimization and achieve common prosperity between urban and rural areas. Urban and rural environmental planning optimization can improve the quality of living environment for urban and rural residents, including air quality, water quality, soil quality, *etc.,* through reasonable layout and design and enhance the quality of life and health level of residents.

The environmental quality directly affects the health and quality of life of residents. Good environmental quality can reduce the harm of air, water, and soil pollution to residents' health, lower the incidence of diseases, and improve their sense of happiness and satisfaction in life. Moreover, good environmental quality is the foundation of sustainable economic development. A high-quality environment helps to enhance the overall image and attractiveness of urban and rural areas, promote the development of ecotourism, ecological agriculture, and ecological industries, and inject new impetus into economic growth.

The goal of optimizing urban and rural environmental planning is to maximize environmental quality, achieve optimal levels of environmental quality indicators (such as air quality, water quality, soil quality, *etc.*), and maximize the quality of life and health of residents. The formula for optimizing the objective function is:

$$F = -w_1 \cdot A + w_2 \cdot B + w_3 \cdot C \tag{7}$$

In formula 7, A, B, and C represent air quality, water quality, and soil quality, respectively, and w_1, w_2, w_3 represent the weights corresponding to the three environmental qualities.

The estimation formula for air quality is expressed as:

$$A = w_{11} \cdot A_1 + w_{12} \cdot A_2 + w_{13} \cdot A_3 + w_{14} \cdot A_4 + w_{15} \cdot A_5 + w_{16} \cdot A_6 \tag{8}$$

In formula 8, A_1, A_2, A_3, A_4, A_5, A_6 represent PM2.5 concentration, PM10 concentration, SO_2 concentration, CO concentration, O_3 concentration, and NO_2 concentration, respectively.

The formula for estimating water quality is expressed as:

$$B = w_{21} \cdot B_1 + w_{22} \cdot B_2 + w_{23} \cdot B_3 \tag{9}$$

In formula 9, B_1, B_2, B_3 represent dissolved oxygen, water quality pH, and total phosphorus, respectively.

The estimation formula for soil quality is expressed as:

$$C = w_{31} \cdot C_1 + w_{32} \cdot C_2 + w_{33} \cdot C_3 \tag{10}$$

In formula 10, C_1, C_2, C_3 represent soil pH, nitrogen content, and phosphorus content, respectively.

Genetic algorithm [25-28] is an optimization algorithm inspired by natural evolution and genetic mechanisms used to solve complex optimization problems. It simulates the process of biological evolution in nature, searching for optimal or approximate optimal solutions through continuous evolution and survival of the fittest. A genetic algorithm encodes candidate solutions in the problem space and continuously generates new solutions through a series of evolutionary operations in order to find the optimal solution to the problem.

The ant colony optimization algorithm [29, 30] simulates the pheromone deposition and volatilization behavior of ants in the process of searching for food, and searches for the optimal solution of the problem through cooperation and information sharing among individuals in the ant colony.

In order to better optimize urban and rural environmental planning, GA and ACO are combined to fully utilize the advantages of the two algorithms and enhance the effectiveness of global search. The optimization process of GA-ACO is shown in Fig. (**2**).

Firstly, bidirectional LSTM is used to predict environmental quality, with the optimization goal of maximizing environmental quality. Excellent individuals can be selected as parents for reproduction based on their fitness function. Cross operations can be performed on the selected parents to generate new offspring individuals, and mutation operations can be performed on the generated offspring to introduce certain random perturbations. Newly generated offspring can be added to the population and some individuals with lower fitness can be discarded. The results of genetic algorithm optimization can be passed into ACO. Each ant makes path selection based on the concentration of pheromones and updates the pheromone concentration on the path according to the ant's selection. It can iterate GA and ACO processes repeatedly to find the optimal solution.

In the process of genetic algorithm optimization, multi--point crossing can be used to exchange the gene sequences of two-parent individuals at multiple crossing points. By performing positional variation operations, the gene values of individuals are changed at gene loci. The genetic algorithm has excellent global search ability and fast solving speed, but it does not make good use of information feedback for adjustment, which may lead to blind optimization direction.

The ant colony optimization algorithm constructs a solution space jointly by multiple ants and achieves information feedback by integrating the pheromones left by multiple ants on the path, thereby improving the optimization effect. This article combines the genetic algorithm with the ant colony optimization algorithm and uses the solution generated by the GA process as the initial information of the ACO algorithm to find the optimal planning solution.

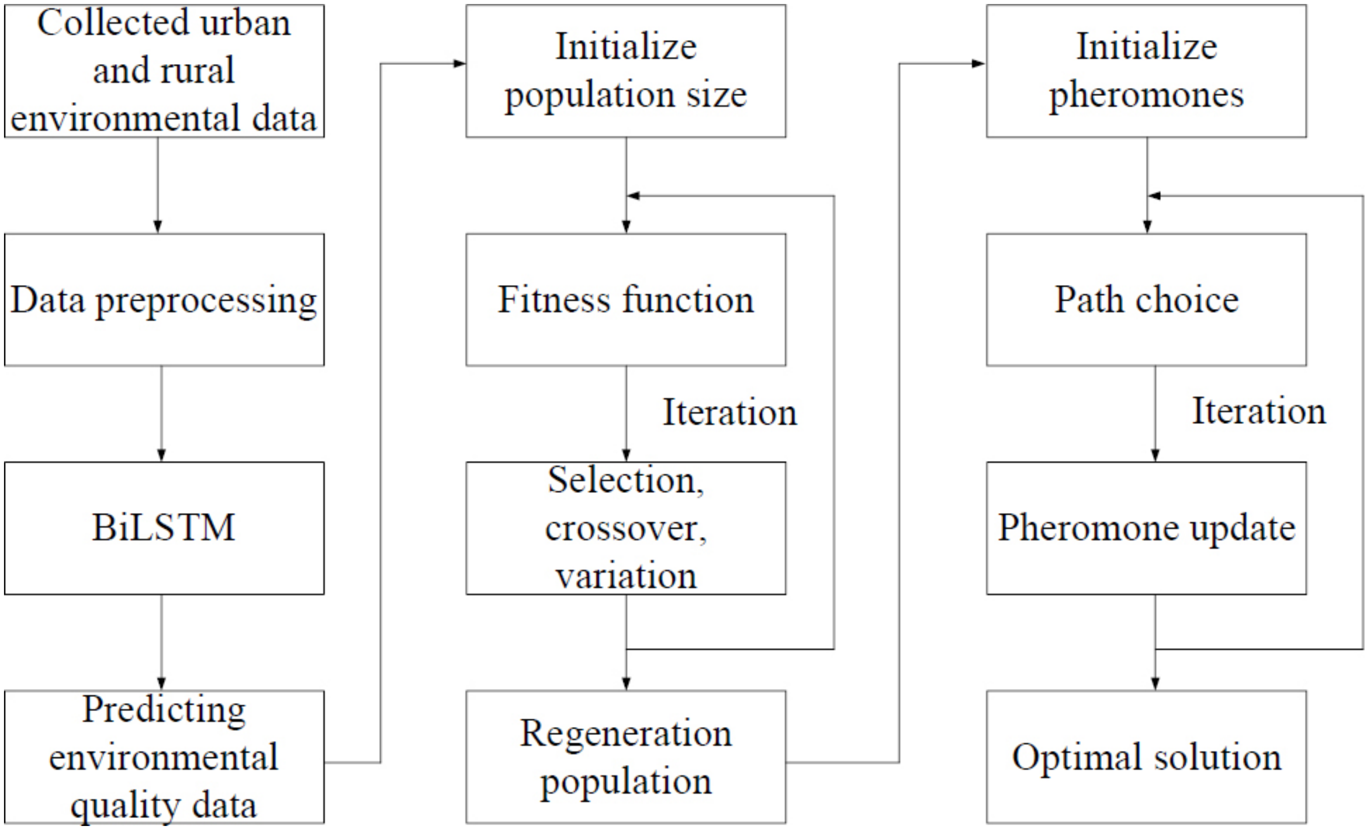

Fig. (2). Optimization process of GA-ACO.

4. EVALUATION OF URBAN AND RURAL ENVIRONMENTAL PLANNING OPTIMIZATION

With the acceleration of economic development and urbanization, the urban population continues to increase, and the problem of urban-rural development imbalance is becoming increasingly prominent. Urban overcrowding and, insufficient resource and environmental carrying capacity have become prominent issues, while rural resource idleness and environmental quality decline have become prominent problems. Therefore, urban and rural environmental planning needs to achieve coordinated development between urban and rural areas through reasonable planning and regulation.

The calculation formula for MSE is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (11)$$

After using BiLSTM to predict urban and rural environmental quality, this article uses GA-ACO to optimize urban and rural environmental planning. In order to effectively highlight the optimization effect of GA-ACO, GA-ACO can be compared with GA and ACO. The goal of optimization is to maximize environmental quality, comparing it from three aspects: air quality, water quality, and soil quality.

In order to better reflect the effectiveness of different algorithms in optimizing urban and rural environmental planning, unoptimized environmental quality data can be used as control data to compare and observe the effects of different optimization algorithms on environmental quality optimization. In addition, in order to comprehensively optimize the performance of the algorithm, the convergence time and number of convergence iterations of the algorithm can be evaluated.

5. RESULTS AND DISCUSSION

5.1. Environmental Quality Prediction Performance

Environmental quality prediction is one of the important means of environmental protection and management. By predicting environmental quality, the development trends and possible changes in environmental problems can be identified in a timely manner, providing a reference for environmental management departments to formulate scientific and reasonable policies and measures. The MSE results of environmental quality prediction are shown in Fig. (**3**).

Fig. (**3**) shows the environmental quality prediction MSE of BiLSTM, LSTM, and GRU models. The bidirectional structure allows BiLSTM to have two hidden states in each time step, allowing for a more comprehensive capture of features in the time series. BiLSTM can be used to predict environmental quality accurately, and timely detect the development trends and possible changes of environmental problems. From the simulation results in Fig. (**4**), we can conclude that the BiLSTM model performs better in environmental quality prediction than the LSTM and GRU models, with the lowest mean square error (MSE) (0.0217). This shows that BiLSTM can better capture long-term dependencies in time series data, more accurately predict the changing trend of environmental quality, and help detect environmental problems in a timely manner.

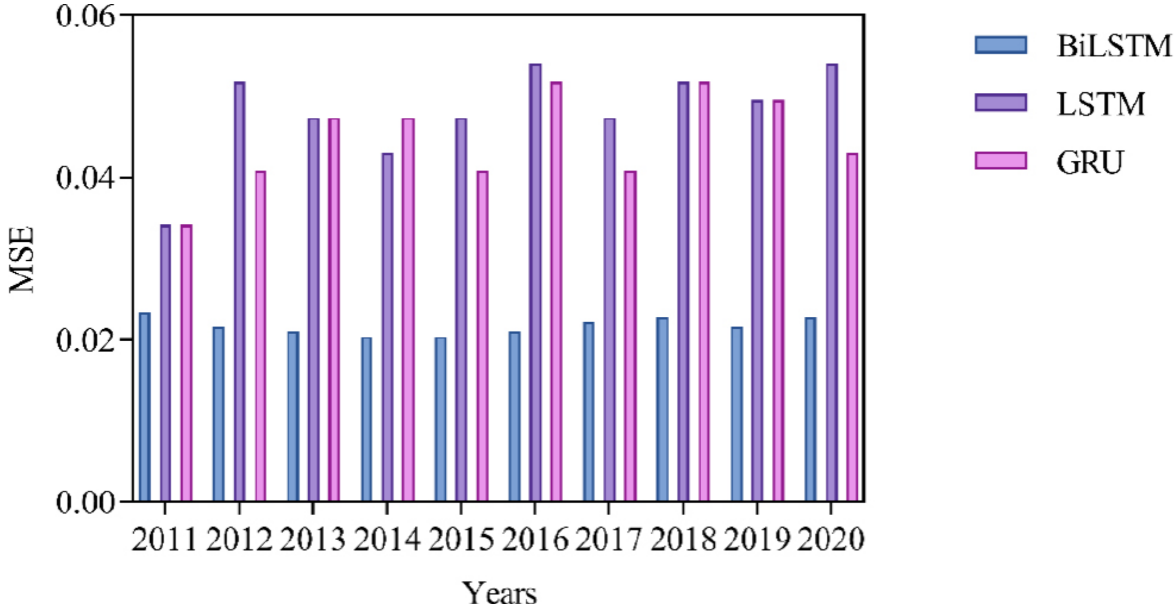

Fig. (3). MSE for environmental quality prediction. *(A higher resolution / colour version of this figure is available in the electronic copy of the article)*.

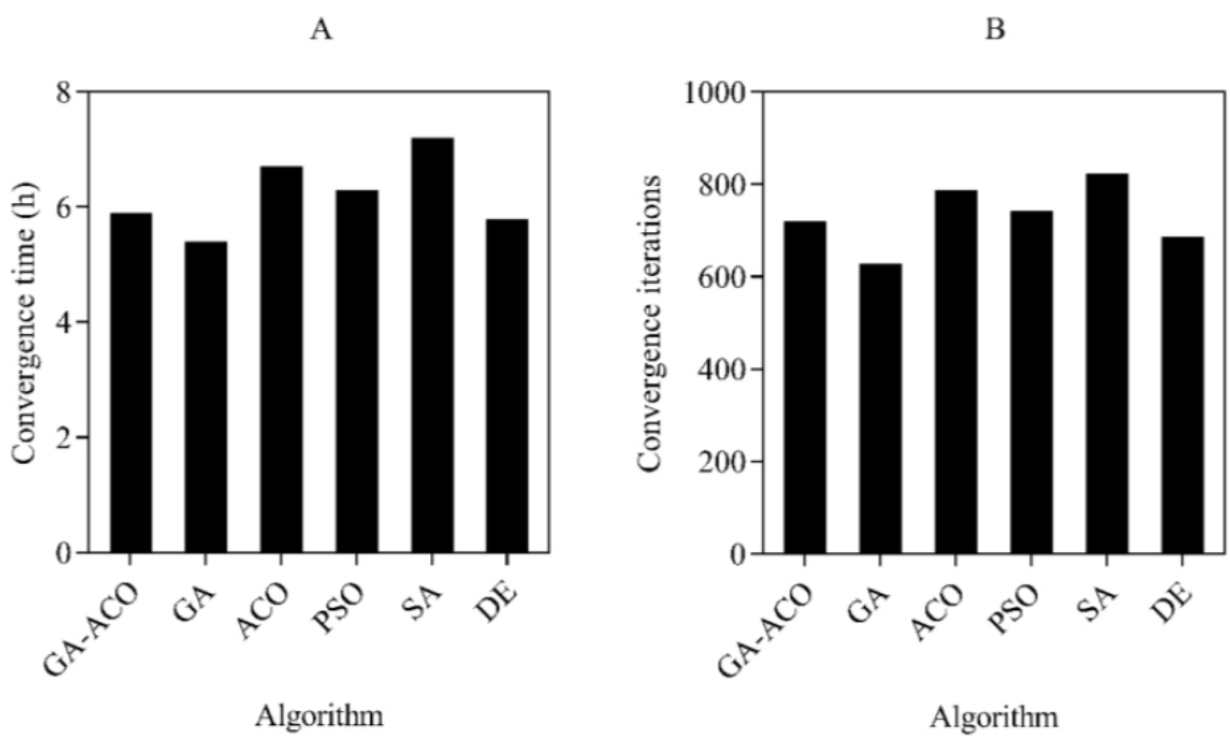

Fig. (4). Convergence time and number of convergence iterations. (**A**) Convergence time (**B**) Convergence iterations. *(A higher resolution / colour version of this figure is available in the electronic copy of the article)*.

5.2. Air Quality Optimization Results

The air quality optimization results of GA are shown in Table **2**.

Table **2** shows the air quality optimization results of GA. Compared to Table **1**, the application of the GA algorithm can comprehensively reduce the content of six air pollution indicators. Genetic algorithms can be used to optimize urban layout, plan spatial structures such as roads, buildings, and green spaces in a reasonable manner, reduce traffic congestion and industrial emissions, and reduce the emission of air pollutants. After GA optimization, the PM2.5 concentration, PM10 concentration, SO_2 concentration, CO concentration, O_3 concentration, and NO_2 concentration in 2020 are 46.4 μg/m^3, 82.0 μg/m^3, 63.1 μg/m^3, 3.9 mg/m^3, 46.1 μg/m^3, and 25.9 μg/m^3 respectively.

The air quality optimization results of ACO are shown in Table **3**.

Table **3** shows the air quality optimization results of ACO. Compared to Table **1**, ACO can also reduce the content of air pollution indicators and improve air quality. The air quality optimized by ACO is worse than that optimized by GA, because ACO tends to perform local search in the search space rather than global search. This leads to ACO being limited by the local optimal solution when looking for the optimal solution, but unable to achieve the global optimal solution. After ACO optimization, the PM2.5 concentration, PM10 concentration, SO_2 concentration, CO concentration, O_3 concentration, and NO_2 concentration in 2020 are 46.9 μg/m^3, 83.3 μg/m^3, 61.8 μg/m^3, 3.9 mg/m^3, 46.6 μg/m^3, and 26.3 μg/m^3 respectively.

GA-ACO was used for urban and rural environmental planning optimization, and the results of air quality optimization are shown in Table **4**.

GA-ACO can effectively improve air quality, and the optimized air pollution indicators of GA-ACO are generally lower than those of GA and ACO. GA-ACO combines the population evolution and crossover operations of genetic algorithms, as well as the pheromone updating and local search strategies of ant colony algorithms. This diverse search strategy can help avoid getting stuck in local optima, increase the coverage of the search space, and improve the probability of finding the global optimal solution. After GA-ACO optimization, the PM2.5 concentration, PM10 concentration, SO_2 concentration, CO concentration, O_3 concentration, and NO_2 concentration in 2020 are 45.7 μg/m^3, 81.6 μg/m^3, 61.8 μg/m^3, 3.6 mg/m^3, 44.9 μg/m^3, and 24.9 μg/m^3 respectively.

Table 2. Optimization results of air quality for GA.

Years	PM2.5 Concentration (μg/m^3)	PM10 Concentration (μg/m^3)	SO_2 Concentration (μg/m^3)	CO Concentration (mg/m^3)	O_3 Concentration (μg/m^3)	NO_2 Concentration (μg/m^3)
2011	64.6	90.8	51.7	3.0	66.3	44.9
2012	62.1	88.3	51.9	3.2	60.6	41.9
2013	59.9	87.5	54.7	3.3	60.9	39.2
2014	57.2	87.8	55.1	2.8	58.2	40.9
2015	57.9	84.1	56.9	3.0	55.9	36.1
2016	53.5	87.5	57.3	3.2	55.9	35.1
2017	54.4	83.2	57.4	3.1	55.3	31.9
2018	50.9	82.8	58.6	3.2	52.6	30.6
2019	49.4	82.8	58.4	3.5	49.9	30.1
2020	46.4	82.0	63.1	3.9	46.1	25.9

Table 3. ACO air quality optimization results.

Years	PM2.5 Concentration (μg/m^3)	PM10 Concentration (μg/m^3)	SO_2 Concentration (μg/m^3)	CO Concentration (mg/m^3)	O_3 Concentration (μg/m^3)	NO_2 Concentration (μg/m^3)
2011	64.7	91.5	51.3	3.1	66.7	46.3
2012	62.6	89.0	51.6	3.2	60.9	42.9
2013	60.6	87.7	53.8	3.3	60.0	39.7
2014	56.6	86.6	53.5	2.9	57.5	39.9
2015	58.2	84.3	56.9	3.1	55.6	35.5
2016	55.0	86.6	57.6	3.3	56.5	35.4
2017	53.1	83.0	58.0	3.2	55.2	33.0
2018	51.7	82.4	59.3	3.8	51.0	30.9
2019	49.6	83.7	58.2	3.7	49.8	29.9
2020	46.9	83.3	61.8	3.9	46.6	26.3

5.3. Water Quality Optimization Results

The water quality is reflected by the content of dissolved oxygen, water pH, and total phosphorus. The optimization results of water quality in 2020 are shown in Table **5**.

Table **5** shows the water quality optimization results for 2020. The higher the dissolved oxygen concentration in the water, the better, with a good range of 6.0-9.0 mg/L. The closer the pH in water is to 7, the better the water quality. Excessive total phosphorus content may lead to eutrophication of water bodies, causing massive algae proliferation and affecting water quality. The dissolved oxygen in urban water after GA-ACO optimization is 7.21 mg/L, and the dissolved oxygen in rural water is 9.23 mg/L, both higher than GA, ACO, and the dissolved oxygen data without optimization. GA-ACO, GA, and ACO can all improve water quality, and GA-ACO has the most significant optimization effect on water quality. The pH of urban water optimized by GA-ACO is 6.7 and total phosphorus is 0.15 mg/L, while the pH of rural water optimized by GA-ACO is 7.0 and total phosphorus is 0.11 mg/L. Therefore, using GA-ACO for urban and rural environmental planning optimization can effectively improve water quality.

5.4. Soil Quality Optimization Results

The optimization results of soil quality in 2020 are shown in Table **6**, which reflects soil quality through soil pH, nitrogen content, and phosphorus content.

Table 4. Optimization results of air quality for GA-ACO.

Years	PM2.5 Concentration (μg/m^3)	PM10 Concentration (μg/m^3)	SO_2 Concentration (μg/m^3)	CO Concentration (mg/m^3)	O_3 Concentration (μg/m^3)	NO_2 Concentration (μg/m^3)
2011	64.3	89.9	50.7	2.5	65.0	44.9
2012	61.6	87.7	51.2	2.6	60.3	41.0
2013	59.6	87.4	53.2	3.1	59.8	38.9
2014	56.5	86.5	53.4	2.6	57.0	39.2
2015	56.3	82.8	55.5	2.6	54.3	34.4
2016	53.4	85.6	57.2	2.7	55.1	34.2
2017	52.7	81.6	57.0	2.7	53.6	31.5
2018	50.5	81.1	57.4	2.8	50.6	29.1
2019	48.8	82.6	57.5	3.2	49.1	29.3
2020	45.7	81.6	61.8	3.6	44.9	24.9

Table 5. Water quality optimization results in 2020.

Type	Water Quality Indicators	GA-ACO	GA	ACO	Not Optimized
Urban	Dissolved oxygen (mg/L)	7.21	7.01	6.78	5.52
	Water quality pH	6.7	6.5	6.4	6.2
	Total phosphorus (mg/L)	0.15	0.19	0.21	0.23
Rural	Dissolved oxygen (mg/L)	9.23	8.84	8.62	7.82
	Water quality pH	7.0	7.1	7.1	7.2
	Total phosphorus (mg/L)	0.11	0.13	0.14	0.15

Table 6. Optimization results of soil quality in 2020.

Type	Soil Indicators	GA-ACO	GA	ACO	Not Optimized
Urban	Soil pH	6.6	5.9	5.7	4.2
	Nitrogen content (g/kg)	1.45	1.89	1.93	2.34
	Phosphorus content (g/kg)	0.42	0.49	0.51	0.57
	Sound pressure level (dB)	45	50	55	65
Rural	Soil pH	6.8	6.5	6.4	5.4
	Nitrogen content (g/kg)	1.23	1.65	1.72	2.44
	Phosphorus content (g/kg)	0.34	0.45	0.47	0.52
	Shannon diversity index	2.75	2.50	2.34	2.21

Table **6** shows the soil quality optimization results for 2020, with the suitable soil pH range for most crops ranging from 5.5 to 7.0. The standard ranges for nitrogen and phosphorus content in soil are 0.10-2.0 g/kg and 0.01-0.5 g/kg, respectively. From the optimization results, it can be seen that GA-ACO can restore the slightly acidic soil environment to a near-neutral soil environment. The pH values of urban and rural soils optimized by GA-ACO are 6.6 and 6.8, respectively. The nitrogen and phosphorus content of the soil that was not optimized exceeded the standard. The application of the three optimization algorithms can reduce the nitrogen and phosphorus content. The nitrogen and phosphorus content after GA-ACO optimization are most significantly reduced, and the application of GA-ACO can effectively improve soil quality. The dynamic nature of factors such as sound pressure levels and biodiversity in ecosystems, affected by climate change or disruptive events such as epidemics, can cause environmental conditions to change dramatically. This variability can render the parameters of optimization methods invalid, limiting their accuracy and relevance.

5.5. Convergence Time and Number of Convergence Iterations

Convergence time and number of convergence iterations are important indicators for evaluating the efficiency of optimization algorithms. Comparing GA-ACO, GA, ACO, PSO, SA, and DE, the convergence time and number of convergence iterations of the optimization algorithm are shown in Fig. (**4**).

In Fig. (**4A**), GA has the shortest convergence time, followed by DE. The convergence times of the six optimization algorithms are sorted from small to large as GA, DE, GA-ACO, PSO, ACO, and SA, with convergence times of 5.4 h, 5.8 h, 5.9 h, 6.3 h, 6.7 h, and 7.2 h, respectively. The GA-ACO algorithm fully utilizes the advantages of the genetic algorithm and ant colony optimization algorithm. The convergence time of GA-ACO is between GA and ACO, but from the perspective of urban and rural environmental planning optimization, GA-ACO is better than GA and ACO. Fig. (**4B**) shows the convergence iterations of different algorithms, with each algorithm having over 600 convergence iterations, while GA has a minimum of 628 convergence iterations. GA adopts a population parallel search approach, where each generation undergoes evolutionary operations on the entire population. Therefore, multiple individuals are searched simultaneously in each generation, accelerating the convergence speed of the algorithm. The convergence iteration number of GA-ACO is 721. To accelerate the convergence speed of the GA-ACO algorithm, we can consider introducing dynamic adjustment strategies, such as adaptive mutation rate and crossover rate, or optimizing the update method of heuristic information. At the same time, the calculation process can be parallelized to improve efficiency.

6. APPLICATION SECTION

Traditional environmental planning methods face many challenges in dealing with environmental problems brought about by urbanization and industrialization. These challenges include the complexity of data, the diversity of environmental factors and the difficulty in predicting their dynamic changes. To this end, this paper proposes to combine the bidirectional long short-term memory network with the genetic algorithm-ant colony optimization algorithm and apply it to urban and rural environmental planning optimization. This combination method not only improves the prediction accuracy but also optimizes the planning scheme and achieves effective response to complex environmental problems.

6.1. Practical Application of BiLSTM in Environmental Quality Prediction

Environmental quality prediction is the basis for formulating effective environmental policies. As an improved long short-term memory network, BiLSTM can consider the past and future information of data at each time step, which makes it perform well in processing time series data. In practical applications, BiLSTM is used to analyze urban and rural environmental data, including air quality, water quality, and soil quality. By training on a large amount of historical data, BiLSTM can accurately predict the changing trend of future environmental quality.

Specific application cases include air quality prediction in Beijing. In this case, the BiLSTM model was used to analyze the time series data of air pollutants such as PM2.5, PM10, and SO_2 in the past few years.

6.2. Practical Application of GA-ACO Algorithm in Environmental Planning Optimization

Environmental planning optimization is a key step in achieving sustainable development. Traditional optimization methods often have difficulty in dealing with complex multi--objective optimization problems. For this reason, GA and ACO are combined and applied to environmental planning optimization, using GA to generate preliminary solutions and then ACO for deep optimization. This method can effectively find the global optimal solution and refine it locally, thereby optimizing the environmental planning scheme.

GA is used to generate a series of preliminary green space layout schemes. These schemes include the distribution location, area, and functional type of green space. Subsequently, the ACO algorithm further optimized these preliminary plans, taking into account factors such as walking paths and green space connectivity. Through this combined approach, the optimized plan not only increased the green space coverage rate but also optimized the spatial layout of green space so that urban green space can better serve the daily activities of residents.

Another application case is in soil management optimization in rural areas. The GA-ACO algorithm is used to optimize soil fertilizer application plans. GA generates a variety of fertilization plans, including the types and application amounts of different fertilizers. ACO performs local optimization based on these plans, taking into account the actual needs of the soil and the growth characteristics of crops. Through this optimization, the final fertilization plan effectively improves soil fertility, reduces environmental pollution, and promotes the healthy growth of crops.

6.3. Practical Application Effects And Future Development Directions

By combining BiLSTM with GA-ACO for environmental planning optimization, this study has achieved remarkable results in practical applications. In the air quality prediction of Beijing, the mean square error of the BiLSTM model is 0.0217, showing a high prediction accuracy. In the optimization of urban green space planning, the GA-ACO algorithm improves the optimization effect of green space coverage and spatial layout so that urban green space can better meet the needs of residents. In rural soil management, the optimized fertilization scheme improves soil fertility and reduces environmental pollution.

CONCLUSION

Urbanization and industrial development pose significant challenges to urban and rural environments, including air, water, and soil pollution. This study aims to enhance environmental quality through optimized urban and rural planning using a Bidirectional LSTM model for data analysis and prediction. The integration of Genetic Algorithm (GA) and Ant Colony Optimization (ACO) (GA-ACO) was found to provide superior environmental quality improvements compared to GA and ACO alone. Although GA-ACO has a longer convergence time than GA, the difference is minor. The use of GA-ACO effectively improves environmental quality and supports sustainable development. Future research should include a broader range of environmental indicators for a more comprehensive assessment.

In the current process of urbanization and industrialization, environmental protection and sustainable development have become the focus of global attention. Although some progress has been made, urban and rural environments still face many challenges, such as air pollution, water pollution and soil degradation. By combining the BiLSTM model and GA-ACO algorithm, this paper shows how to optimize urban and rural environmental planning and significantly improve environmental quality. This method not only shows superiority in air, water and soil quality optimization but also shows outstanding performance in optimization efficiency. However, future development should be more comprehensive and diversified, covering more environmental indicators to provide a more comprehensive environmental quality assessment. In addition, technological progress will further promote the development of intelligent environmental monitoring and forecasting systems, such as the Internet of Things and big data analysis, and apply real-time data to environmental quality forecasting and optimization, so as to improve the scientificity and timeliness of planning. On the policy level, we should strengthen the policy orientation of coordinated development between urban and rural areas, promote the balanced allocation of resources and, improve the ecological compensation mechanism, and fundamentally solve the problem of unbalanced development between urban and rural areas. Future research should also pay attention to public participation and promote the whole society to work together for environmental protection and sustainable development by improving public awareness and participation. In addition, interdisciplinary cooperation will become a trend, and collaborative innovation in environmental science, computer science, economics and other fields will provide a more comprehensive and systematic solution to environmental problems. To sum up, future development needs comprehensive technical progress, policy support and public participation to form a multi-level and multi-field collaborative mechanism to achieve the real, sustainable development goal.

AUTHORS' CONTRIBUTIONS

Feng Zhao wrote the paper and Chuanlong Han collected the data.

LIST OF ABBREVIATIONS

GA-ACO	=	Genetic Algorithm-Ant Colony Optimization
MSE	=	Mean Squared Error

CONSENT FOR PUBLICATION

Not applicable.

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CONFLICT OF INTEREST

The authors declare no conflict of interest, financial or otherwise.

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