Impact of Agricultural Big Data Analysis on Urban Development

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***Abstract*—As an emerging technological approach, agricultural big data analysis provides new possibilities for urban development. This paper systematically elaborates on the applications of agricultural big data analysis in optimizing urban development, improving resource utilization, and enhancing urban environmental sustainability. It explores the impact of agricultural big data analysis on urban development. The paper describes the current state of agricultural big data analysis in Jiaozuo City in detail and, through detailed case studies, such as using the support vector machine (SVM) model to optimize irrigation water, the results indicate a reduction of 34.75 m^3/ha in total water consumption and an average reduction of 5.79 m^3/ha per sample. By calculating the optimal path of the agricultural product supply chain using the ant colony algorithm, the shortest and longest distribution paths of the agricultural product supply chain planned in this paper differ by 200%. The research shows that agricultural big data analysis significantly optimizes resource allocation, promotes the coordinated development of cities and agriculture, ensures the safety of urban resources such as food, and supports the sustainable development of cities. Finally, suggestions are made for further exploration in this field by the government, enterprises, and research institutions. The development of this technology can provide innovative solutions for urban development.**

***Index Terms*—Agricultural big data analysis, Urban development, Decision support**

I. Introduction

Cities and agriculture are inextricably linked. Agriculture is an important supplier to cities, while cities are the main consumers and markets for agricultural products. Therefore, fully leveraging the role of big data analysis of agriculture-related data in agricultural applications can not only promote the development of agriculture but also have a profound impact on urban growth. With the rapid development of information technology, agricultural big data analysis, as an emerging technological approach, can provide decision-makers and agricultural producers with new solutions by collecting, processing, and analyzing large-scale agricultural data, improving the efficiency and quality of agricultural production, and achieving refined agricultural management [1], [2]. This paper aims to explore the facilitating role of agricultural big data analysis in urban development and provide theoretical and practical support for promoting sustainable urban development, optimizing urban planning, and improving the quality of urban life.

II. Literature Review

The application of digital technology has not only promoted the improvement of environmental governance and public service quality but also enhanced the efficiency of urban governance and the development of agriculture and rural areas. Feng Chao-Rui (2022), based on the TOE (technology, organization, environment) framework and using the NCA(Necessary Condition Analysis) and fsQCA(Fuzzy-Set Qualitative Comparative Analysis) methods, deeply explored the influencing factors and advancement paths of high-level digital government construction in 31 provinces (municipalities and autonomous regions) in China. The research shows that policy drive is a necessary condition for digital government construction, and technological capability and fiscal supply capacity, together with policy drive, are the key conditions for rapidly advancing digital government construction [3]. Li Xu-Hui et al. (2023), using the Dagum Gini coefficient and Kernel density estimation method, analyzed the regional differences and dynamic evolution trend of China's rural digital transformation from 2011 to 2020. The research found that although China's rural digital transformation index showed a significant upward trend, regional differences were still evident, and there was a polarization phenomenon. The research helps to diagnose the current stage and evolution trend of rural digital transformation in China as a whole and in the four major regions, providing an experience for comprehensively promoting the rural revitalization strategy and the regional coordinated development strategy to achieve a win-win situation in the new era [4]. Chen Chao-Bing et al. (2023), through case studies, explored how digital technology improves the quality of rural public services. They found that digital technology effectively solves the problem of low quality of rural public services through expression empowerment, decision-making empowerment, matching empowerment, and evaluation empowerment, promoting the high-quality supply of public services [5]. Zhang Yue et al. (2024) explored the application of the multi-center governance model in rural environmental governance. They pointed out that the traditional government single-center governance model has many limitations, while the multi-center governance model can improve the adaptability of rules and the effectiveness of supervision, thereby enhancing the effectiveness of environ-

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mental governance. Digital technology, through information effects and channel effects, can effectively solve the problems of expected benefits and expected costs, thus promoting the digital transformation of rural environmental governance [6]. Su Lan-Lan (2023) explored the role of digital governance in improving the efficiency of rural governance, proposed a framework for analyzing the efficiency of digital governance in "concept-structure-method-result-mechanism," and suggested improving the efficiency of rural digital governance through systematic thinking, dialectical thinking, and innovative thinking [7].

III. Agricultural Big Data Analysis and Urban Development

A. Overview of Agricultural Big Data Analysis

Agricultural big data analysis refers to the use of modern information and data analysis technologies to collect, process, and analyze large-scale, multi-dimensional data generated in the agricultural production process, thereby obtaining valuable information and knowledge to assist decision-makers in scientific production, management, and decision-making [8], [9].

The main technical means include real-time collection of multi-dimensional data such as soil moisture, temperature, weather conditions, and crop growth status through the Internet of Things (IoT), remote sensing technology, and drones for data collection. Data cleaning, preprocessing, and storage technologies are used to denoise, complete, and standardize the collected raw data to ensure data quality and consistency. Mathematical modeling and in-depth analysis of the processed data are performed using machine learning, statistical analysis, and other techniques, such as predicting agricultural product yield through regression analysis, using cluster analysis for classified management of different farmlands, and utilizing time series analysis to predict market demand. The analysis results are visually presented in the form of charts, maps, etc., to help decision-makers and farmers quickly understand and utilize the data for data visualization.

The main functions include analyzing crop soil, climate change, crop growth, and other data in production management to achieve precise fertilization and other management, improving agricultural product yield and quality. Disease and pest monitoring, early warning, and epidemic analysis and prediction are realized to reduce crop losses. Continuously analyzing market demand, price trends, and other data to guide agricultural product sales, achieving a balance between agricultural product supply and demand and market risk assessment. Based on the monitored data, the agricultural industry structure and resource allocation are analyzed to provide a scientific basis for government management and decision-makers to formulate development policies and plans.

B. Relationship between Agricultural Big Data Analysis and Urban Development

Agricultural big data analysis and urban development are closely related, mainly in the following aspects [11], [12]: Firstly, it ensures a good agricultural supply for cities. As an important supplier to cities, agricultural big data analysis can help improve the yield and quality of agricultural products and ensure the living needs of urban residents. For example, by analyzing soil and meteorological data, precise fertilization and pesticide spraying can be carried out to increase the yield and quality of grain and vegetables, ensuring food safety in cities. Secondly, by monitoring farmland conditions through remote sensing technology and drones, implementing precise fertilization and irrigation, and reducing the waste of resources such as fertilizers and pesticides, environmental pollution can be reduced, and reasonable allocation of resources can be promoted, optimizing the utilization of agricultural resources and improving the efficiency of production resource utilization. Thirdly, through big data analysis, agricultural production methods can be optimized, the use of chemicals can be reduced, soil and water sources can be protected, and the quality of the ecological environment around cities can be improved, promoting the sustainable development of the urban environment. Finally, by analyzing and predicting agricultural market demand data, farmers can be guided to plant high-value-added crops and increase their income, narrowing the urban-rural income gap and promoting the common prosperity of urban and rural economies, and promoting the coordinated development of cities and rural areas.

C. Current Status of Agricultural Big Data Analysis and Urban Development at Home and Abroad

Since China proposed the "Internet + Agriculture" strategy in 2015, it has made remarkable achievements in promoting agricultural modernization and digitalization. Taking Henan Province as an example, the province has strengthened the application and industrial promotion of agricultural big data by implementing the "Internet + Agriculture" action plan. The government encourages agricultural enterprises and scientific research institutions to use big data technology to optimize processes in agricultural production and improve the efficiency and quality of agricultural production. At the same time, the government has introduced a series of supporting policies, such as providing financial support, tax reductions, and exemptions, and establishing agricultural data-sharing platforms, to provide a good policy environment and industrial ecology for the development and application of agricultural big data [13], [14].

In the United States, the agricultural sector has always attached great importance to technological innovation and data application. Taking California as an example, the state government actively promotes the integration of agricultural big data analysis and technological innovation by establishing agricultural science and technology parks and promoting cooperation between universities and agricultural enterprises. The government encourages agricultural enterprises and startups to use big data technology to carry out innovative projects such as smart planting of agricultural products, precision fertilization, and smart irrigation. At the same time, the California government has also strengthened the supervision of data privacy protection in agricultural production to ensure the data

security of farmers and enterprises and promote the reasonable utilization and industrial development of agricultural data [15], [16].
As a country with highly developed agriculture, the Netherlands is committed to combining agricultural data with advanced technology to promote the intelligent and sustainable development of agricultural applications. At the Agricultural Innovation Center in Amsterdam, researchers have established an agricultural data integration application platform using blockchain technology and Internet of Things technology. The platform integrates data from various aspects such as agricultural production, market demand, and environmental monitoring, realizing full-process monitoring and management of agricultural production. This application not only improves the quality and safety of agricultural products but also promotes the traceability of agricultural products, enhancing consumers' trust in agricultural products. The Netherlands' agricultural data integration application provides advanced technical support and demonstration for global agricultural development [15], [16].

IV. Decision-Making Use of Agricultural Big Data Analysis

A. Data Cleaning and Preprocessing [16].

Data cleaning and preprocessing is the first step in data analysis, with the purpose of ensuring data quality. Common methods include missing value processing, outlier detection and processing, and data normalization [15]. The role of data cleaning is mainly to remove invalid values and outliers and fill in missing data. Missing value imputation often uses the mean imputation method, such as:

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

Outlier detection often uses the standard deviation method, such as:

$$x = x_i | |x_i - \mu| > 3\sigma \tag{2}$$

where μ is the mean, and σ is the standard deviation.

B. Data Exploration and Visualization.

This step mainly displays the distribution characteristics and regularity of the data through statistical analysis and graphical representation. Common methods include histograms, scatter plots, and box plots. Histograms are often used to display the distribution of univariate data, such as plotting a histogram of soil moisture values in farmland to understand the distribution of soil moisture. Scatter plots are often used to display the relationship between two variables, such as plotting a scatter plot of nitrogen content in soil and crop yield to clearly observe the relationship between them. Box plots are often used to display the central tendency and dispersion of data and detect outliers, such as plotting box plots of soil pH values in different farmland areas to compare the differences in soil acidity and alkalinity between regions.

C. Data Analysis and Modeling

This step is the core part, which deeply explores data relationships through mathematical modeling and statistical analysis. Common methods include regression analysis, cluster analysis, principal component analysis, decision trees, etc., which can predict trends and provide a scientific basis.
For example, linear regression is used to analyze the relationship between variables and is often used to predict the impact of soil nutrients on yield. The mathematical formula is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon \tag{3}$$

where y is the agricultural product yield, x_i are the influencing factors, β_i are the regression coefficients, and ε is the error term.
The ARIMA model of time series analysis is used to predict time series data and can be used to analyze the impact of temperature and rainfall on crop growth. The commonly used mathematical formula is:

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{4}$$

where y_t is the time series value, ϕ_i are the AR term coefficients, θ_i are the MA term coefficients, and ε_t is the error term.
K-means cluster analysis can be used to divide farmland data into different regions for refined management. The commonly used mathematical formula is:

$$\min \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2 \tag{5}$$

where k is the number of clusters, C_j is the j-th cluster, and μ_j is the mean of the j-th cluster.

D. Decision Support and Optimization

This step interprets and utilizes the analysis results to provide suggestions and optimization solutions for decision-makers. Common mathematical methods include multi-objective optimization, risk analysis, decision tree models, etc., which help evaluate and select the optimal solution. Here, we use a multiple linear regression model to analyze agricultural data as an example:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{6}$$

where Y is the predicted dependent variable (such as agricultural product yield); $X_1, X_2, \ldots, X_n$ are the independent variables (such as temperature, rainfall, fertilizer application); β_0 is the intercept term, indicating the expected value of the dependent variable when all independent variables are zero; $\beta_1, \beta_2, \ldots, \beta_n$ are the regression coefficients, indicating the degree of influence of the independent variables on the dependent variable; and ε is the error term, representing the influence of other unexplained factors on the dependent variable. If further detailed explanation is needed, the matrix representation can be introduced to make the formula more concise and easier to calculate:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{7}$$

where $\mathbf{Y}$ is the vector of the dependent variable, $\mathbf{Y} = (Y_1, Y_2, \ldots, Y_n)^T$, where Y_i represents the dependent variable of the i-th observation. $\mathbf{X}$ is the design matrix containing the independent variables, $\mathbf{X} = \begin{pmatrix} 1 & X_{11} & X_{12} & \cdots & X_{1n} \\ 1 & X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{m1} & X_{m2} & \cdots & X_{mn} \end{pmatrix}$, where each row represents an observation, and each column represents an independent variable. The first column is all 1's for the intercept term β_0. $\boldsymbol{\beta}$ is the vector of regression coefficients, $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2, \ldots, \beta_n)^T$, and $\boldsymbol{\varepsilon}$ is the vector of error terms, $\boldsymbol{\varepsilon} = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_m)^T$.

In practical applications, the multiple linear regression model can be used to scientifically analyze agricultural data and provide a basis for decision-making, for example, by analyzing factors such as temperature, rainfall, and fertilizer application on agricultural product yield, and optimizing these factors to increase yield and control costs.

V. Current State of Agricultural Big Data Analysis and Urban Development in Jiaozuo City

Jiaozuo City is located in the northwestern part of Henan Province, at the southern foot of the Taihang Mountains and the northern bank of the Yellow River. It has a good agricultural foundation and suitable climatic conditions. As part of an agricultural province, Jiaozuo City has actively promoted the application of agricultural big data analysis in recent years, optimizing agricultural production management and the agricultural product transportation supply chain, improving agricultural production efficiency, and promoting the coordinated development of urban and rural areas.

A. Current State of Big Data Construction in Jiaozuo City

In recent years, Jiaozuo City has made significant progress in the construction of big data infrastructure by strengthening the coverage of optical fiber networks and wireless networks, providing a strong guarantee for the efficient operation of data centers and big data platforms, and ensuring the basic network environment for big data applications. At the same time, the Jiaozuo City government has actively introduced various measures and policies to support the development of the big data industry. It has issued policy documents such as the "Implementation Plan for the Construction of a New Smart City in Jiaozuo City" and the "Implementation Plan for Strengthening the Construction of Digital Government in Jiaozuo City" to accelerate the development of the big data industry by providing financial support, tax incentives, and land policies, encouraging enterprises to carry out the construction and operation of big data projects in Jiaozuo City. The "Development Plan for Strategic Emerging Industries and Future Industries in Jiaozuo City during the 14th Five-Year Plan Period" and other documents detail the development goals and implementation paths of Jiaozuo City's big data industry in the next few years, including infrastructure construction, application scenario promotion, and technological innovation. Through cooperation with Henan Polytechnic University and other universities and research institutions, big data professionals are cultivated to enhance the research development and application capabilities of big data technology.

B. Current State of Agricultural Big Data Application in Jiaozuo City

Under the guidance of the "Internet + Agriculture" strategy, the Jiaozuo City government utilizes the smart agricultural big data center to improve agricultural production efficiency by integrating data on soil, weather, crop growth, etc., and providing precise management suggestions and scientific decision support [15], [16].

For example, Wuzhi County actively plans and implements high-efficiency water-saving irrigation projects. The county has built a smart agricultural platform in the demonstration area, using satellite remote sensing technology to monitor soil moisture, crop conditions, and pest and disease situations. Through big data analysis, fully automated control is realized, with timely irrigation and fertilization, and timely release of pest and disease early warnings. Wenxian County has built a smart agricultural platform to assist in the sales of agricultural products such as yam, greatly improving the efficiency of agricultural production in Jiaozuo City and the quality of agricultural products. The platform's data analysis function has helped farmers reduce blindness in agricultural production and increase their income levels. Based on this, Jiaozuo City not only ensures the food supply for urban residents but also promotes the coordinated development of urban and rural economies, contributing to the good development of the city.

C. Case Study Analysis

Taking the Jiaozuo government's need to optimize agricultural irrigation water supply and agricultural product supply chain as an example, the efficiency of resource utilization can be improved. Here, we can choose the support vector machine (SVM) to predict crop water demand and the ant colony optimization algorithm to predict the optimal path of the agricultural product supply chain and optimize them respectively.

Support vector machine (SVM) is a commonly used supervised learning method, mainly used for classification and regression tasks, which are the two most important types of supervised learning tasks. In regression tasks, it is called support vector regression (SVR). SVR uses SVM to fit curves and perform regression analysis, with the goal of finding a function that fits the data as closely as possible within the maximum deviation of the given data points and predicts the actual output value as accurately as possible.

The mathematical formula for the SVR optimization problem can be expressed as:

TABLE I
CROP WATER DEMAND

Soil Moisture (%)	Temperature (°C)	Rainfall (mm)	Crop Water Demand (m^3/ha)
20	22	5	300
25	23	10	280
30	21	0	350
35	24	3	320
40	25	8	300
45	26	12	270

$$\min_{\omega,b,\xi,\xi^*} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$$

$$subject \quad to \quad y_i - (\omega^T x_i + b) \le \varepsilon + \xi_i$$

$$(\omega^T x_i + b) - y_i \le \varepsilon + \xi_i^*$$

$$\xi_i, \xi_i^* \ge 0 \; for \quad all \quad i$$

Fig. 1. SVR optimization

As Figure 1, where $\mathbf{w}$ is the weight vector, b is the bias, ξ_i and ξ_i^* are slack variables, C is the regularization parameter that controls the trade-off between model complexity and error. The final SVR decision function is:

$$f(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b \tag{8}$$

In the application of optimizing water resource management, the actual values are used to establish and validate the accuracy of the model, while the predicted values are used in practical applications to assist in decision-making, such as adjusting irrigation plans to reduce water waste and ensure healthy crop growth. Using the above support vector regression principle mathematical model, modeling and analysis are performed using MATLAB, and the results are shown in Figures 2 and 3.
Note: Table I shows the water demand of a certain crop under different soil moisture, temperature, and rainfall conditions. The "Crop Water Demand (m^3/ha)" provided in the table represents the actually observed or collected data, which are used to train the support vector regression model. After using the model for training, the model will output the predicted crop water demand based on the input soil moisture, temperature, and rainfall.

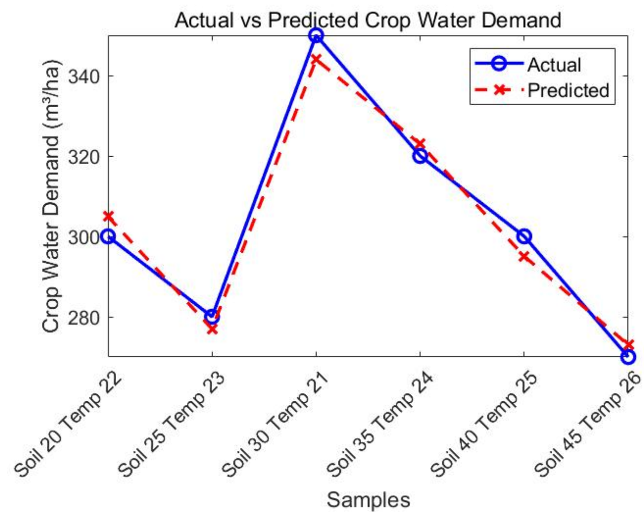

Fig. 2. Comparison of crop water demand predicted by the SVR model with actual demand

Figure 2 shows the comparison between the crop water demand predicted by the SVR model and the actual demand. It can be seen that the model's predicted values are highly consistent with the actual values, indicating that the model has high prediction accuracy.

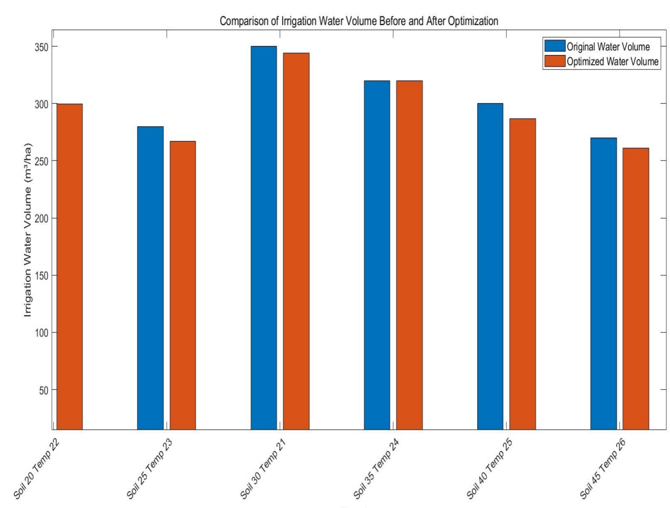

Fig. 3. Comparison of irrigation water consumption before and after optimization

Figure 3 shows the comparison of irrigation water consumption before and after optimization. Through optimization, the irrigation water consumption of each sample has decreased to varying degrees. The total reduction is 34.75 m^3/ha (the sum of water savings for all samples), and the average reduction is 5.79 m^3/ha (the average water savings per sample). Through agricultural big data analysis and optimization, we can significantly reduce irrigation water consumption and achieve the goal of saving water resources. Through optimization, unnecessary irrigation water use is reduced, and the utilization efficiency of water resources is improved. Optimizing the supply chain path of agricultural products is also an important function of agricultural big data analysis to optimize the urban agricultural product supply.

Here, we use the ant colony algorithm to analyze the efficiency of the agricultural product supply chain and propose optimization solutions.

(1) In this case, a simplified cost model is used to represent the total cost of the supply chain. The model can be expressed by the following formula:

The total cost (TC) is the sum of the fixed cost (FC) and the variable cost (VC):

$TC = FC + VC$.

The variable cost is proportional to the logistics distribution distance, $VC = k \times D$; the total cost after optimization is $TC_1 = FC + k \times D_1$.

where k is the cost coefficient per unit distance, D is the logistics distribution distance, and the length of the optimized logistics distribution route is D_1.

(2) The ant colony optimization algorithm is used to find the optimal path. The following parameters are defined:

$G = (V, E)$:

G represents the distribution network, where V is the set of nodes (distribution centers and customers), and E is the set of edges (distribution paths).

d_{ij} is the distance from node i to node j; τ_{ij} is the pheromone intensity on edge (i, j); η_{ij} is the desirability of edge (i, j) (usually $1/d_{ij}$); α is the importance factor of pheromone; β is the importance factor of desirability; ρ is the pheromone evaporation coefficient; Q is a constant used to calculate the pheromone increment; m is the number of ants.

(3) Objective Function The objective is to find the minimum total distribution cost, i.e., the shortest path.

$$\min \sum (i, j) \in pD_{ij} \tag{9}$$

where P is a valid distribution path.

(4) Ant Colony Optimization Calculation

In the first step, initialization, a small amount of pheromone is initialized on each edge:

$\tau_{ij}(0) = \tau_0$.

In the second step, solution construction, each ant starts from the starting node and probabilistically selects the next node until all nodes are visited. The selection probability $p_{ij}(t)$ is defined as:

$$p_{ij}(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i(t)} [\tau_{il}]^\alpha [\eta_{il}]^\beta} \tag{10}$$

where N_i is the set of neighbor nodes of node i.

In the third step, pheromone update, a pheromone is evaporated on all paths,

$\tau_{ij}(t)(t+1) = (1-\rho)\tau_{ij}(t)$;

pheromone is added based on the ants' paths,

$\tau_{ij}(t)(t+1) = \sum_{k=1}^{m} \Delta\tau_{ij}^k$.

where $\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L_k}, & \text{if ant } k \text{ passes edge } (i,j) \\ 0, & \text{otherwise} \end{cases}$, and L_k is the path length of ant k.

In the fourth step, iteration, steps 2 and 3 are repeated until the termination condition is met (e.g., number of iterations or computation time).

TABLE II
DISTRIBUTION NETWORK DISTANCE

Node	Node 1	Node 2	Node 3	Node 4	Node 5
Node 1	0	2	2	5	7
Node 2	2	0	4	8	2
Node 3	2	4	0	1	3
Node 4	5	8	1	0	2
Node 5	7	2	3	2	0

Based on the mathematical principles of the ant colony algorithm, modeling, and analysis are performed using MATLAB software, and the optimal path analysis results are shown in Figure 4.

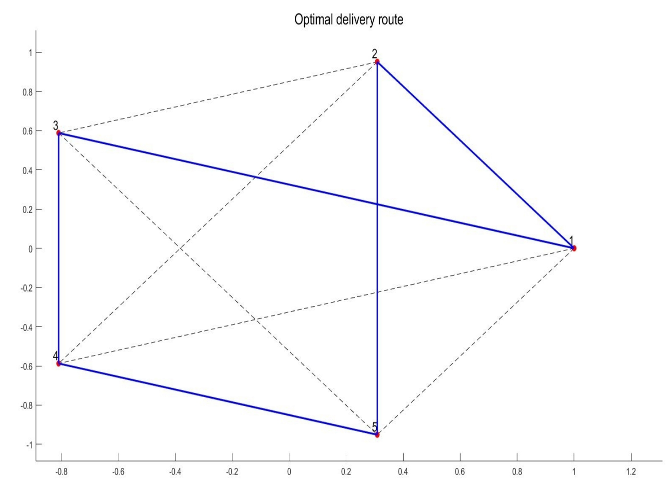

Fig. 4. Optimal distribution path model

In Figure 4, the red dots denote the nodes in the distribution network, which include both distribution centers and customers. These nodes are connected by the optimal distribution path, represented by the blue solid lines. This path is determined using the ant colony algorithm, which calculates the shortest route that visits all the nodes. In contrast, the black dashed lines signify potential paths between nodes, but they are not part of the optimal solution.

The optimal path begins at Node 1 and follows the sequence 1→3→4→5→2→1, completing a circuit that starts and ends at the same node. The total distance covered by this optimal path is 9 units. To find the longest possible path, a MATLAB calculation was performed, revealing that the route 5→3→2→4→1 has the greatest distance of 27 units.

The successful application of the ant colony algorithm demonstrates its effectiveness in determining the optimal path from the starting point to all other nodes in the distribution network. By identifying the shortest route, this approach helps to minimize the overall logistics distribution costs and enhance the efficiency of the agricultural product supply chain. The optimized path ensures that products are delivered to customers in a timely manner while reducing unnecessary transportation expenses.

Furthermore, the visual representation of the distribution network and the optimal path provides valuable insights for decision-makers. It allows them to understand the connectivity between distribution centers and customers, identify potential bottlenecks, and make informed choices regarding resource allocation and network expansion. By leveraging the power of optimization algorithms like the ant colony algorithm, businesses can streamline their logistics operations, improve customer satisfaction, and gain a competitive edge in the market.

VI. Conclusion

This paper systematically explores the role of agricultural big data analysis in urban development and demonstrates the important contributions of this emerging technology in optimizing urban development, enhancing resource utilization around cities, and other aspects. Through case studies of the use of agricultural big data analysis in urban development decision-making, the steps and results are explained in detail, showing the positive role of data analysis in optimizing the utilization of various resources in urban development.

At the same time, taking Jiaozuo City, Henan Province as an example, the current state of agricultural big data analysis application in Jiaozuo City is introduced. Through detailed explanations and case studies of the use of agricultural big data analysis in decision-making, such as using the support vector machine (SVM) model to optimize irrigation water and predict crop water demand, the results show a reduction of 34.75 m^3/ha in total water consumption and an average reduction of 5.79 m^3/ha per sample; by calculating the optimal path of the agricultural product supply chain using the ant colony algorithm, the shortest and longest distribution paths of the agricultural product supply chain planning in this paper differ by 200%, which can effectively reduce the total distribution cost.

In view of the important role of agricultural big data analysis in urban development, the government should formulate relevant policies and measures to strengthen the guidance and support for agricultural big data analysis technology, encourage agricultural enterprises and research institutions to strengthen innovation cooperation, promote the integration of production practice, strengthen the supervision of agricultural data security and privacy protection, and promote the sharing and interoperability of agricultural data resources.

In the future, with the continuous advancement of technology and the deepening of applications, agricultural big data analysis will play an increasingly important role in promoting sustainable urban development, optimizing urban development planning, and improving the quality of life of residents. Future related research can focus on strengthening cross-disciplinary cooperation, promoting the integrated application of agricultural data with urban planning, environmental protection, food safety, and other fields, and promoting the development of smart agriculture and smart cities. If conditions permit, the application case studies can be expanded to provide more reference and reference for agriculture to promote urban development in different regions.

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