Design and Application of Wireless Network Planning Model Based on Spatial-Temporal Analysis and Data Mining: New Solutions to Improve Network Security

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(Received Nov. 17, 2023; Revised and Accepted Nov. 21, 2024; First Online Dec. 24, 2024)

Abstract

With the rapid development of wireless network technology, the problem of network security has become increasingly prominent, which poses a higher challenge to wireless network planning. However, the performance of the current wireless network planning model is insufficient. In order to improve the planning effect of the wireless network planning model, this study will use space-time analysis to predict the passenger traffic of the base station, and use data mining technology to build a signal quality detection model. Finally, the two models are integrated to build a new wireless network planning model. The results show that the root-mean-square error of the proposed model is 0.12, which is significantly lower than 0.84 of the comparison model. The results show that the signal quality and cost-benefit indexes of the proposed wireless network planning model are 8.8 and 8.9 points, respectively, which are better than the comparison model. The above results show that the wireless network planning model proposed in this study can not only optimize the network coverage and capacity but also significantly improve the security performance of the network, providing a strong guarantee for the safe operation of the wireless network.

Keywords: Data Mining; Flow Forecast; Network Planning; Network Security; Spatio-temporal Analysis

1 Introduction

In the era of "mobile changes life", wireless network has become an indispensable part of people's life. However, with the expansion of network scale and the growth of user demand, wireless network planning is faced with unprecedented challenges, especially the increasingly prominent problem of network security [18]. Traditional network planning methods often neglect the importance of network security, which leads to the network being vulnerable to various security threats during operation.

In order to solve this problem, a wireless network planning model based on space-time analysis and data mining came into being [4]. Spatio-temporal analysis is a research method on the ground of temporal and spatial information, which can help to gain insight into the spatial-temporal characteristics in wireless networks [2]. By collecting and analysing data such as user behavior, base station distribution and signal strength, the temporal and spatial distribution laws of user activities can be found [11]. These laws can provide an important reference basis for wireless network planning. However, only relying on spatial-temporal analyses is not enough to solve the problems of base station location adjustment and weak coverage. At this point, the application of DM techniques becomes particularly important.

DM is a process of discovering patterns and knowledge from large-scale data, which can help to dig out the valuable information hidden behind the data [1]. Through DM, the operational data of wireless networks can be transformed into predictable patterns and network planning can be performed on the ground of these patterns [5]. On the ground of the above background, this study proposes a wireless network planning model on the ground of spatial-temporal analysis and DM, which aims to solve the problems of weak coverage areas and base station location adjustment. The core of the model is a base station human traffic prediction model on the ground of spatial-temporal analysis and an RPMA low-power WAN network planning method on the ground of DM. The innovation of this research is to use spatial-temporal features and DM techniques to solve the problems of weak coverage and base station location adjustment in wireless networks, and to improve network performance and user experience.

The article consists of four, the first is an analysis of spatial-temporal analysis techniques, DM techniques, and research in the field of wireless network planning; the second part is mainly the design process of the wireless network planning model integrating spatial-temporal analysis and DM; the third part is the analysis of the performance test of the model on the ground of spatial-temporal analysis and DM; and the fourth part is the summary of the whole paper.

2 Literature Review

With the further development of spatial-temporal analysis techniques, its application is getting wider and wider. Baumgertel's team proposed a fuzzy logic based spatial-temporal analysis technique in order to better analyse the susceptibility of different seasons to future wind erosion, through which the future wind erosion susceptibility of different seasons was analysed, and the results showed that climate sensitivity to wind erosion is bound to increase significantly in the late 21st century during the growing seasons. Umunnakwe et al. presented a prediction model on the ground of data-driven and spatial-temporal analysis techniques to reduce the threat of wildfires to the stability of the power grid, through which the model predicts wildfires so as to take appropriate measures for ensuring the security of the power grid, and the performance analysis of the proposed prediction model found that, compared with other prediction models, the accuracy of this model in the detection of potential wildfires was 99.5%, and it can achieve the risk-aware operation of the power system [16]. Moreover, with the rapid development of computer technology, DM technology is also applied in many fields. Nancy team for the wireless sensor network intrusion detection system detection performance is poor, put forward a DM based detection algorithm, the detection algorithm empirical analysis, the results show that the detection algorithm's false alarm rate, energy consumption and delay are lower than the traditional detection algorithms, which has an important practical value [10]. Riyaz *et al.* presented a new intrusion detection system on the ground of DM technology and feature selection algorithm in order to identify intruders in wireless networks more effectively. The practical application effect of the system was tested and the outcomes showcase that the overall detection accuracy of this intrusion detection system was as high as 98.91%, which was much higher than that of the compared intrusion detection models [14].

As the boost of wireless network technology, more and more scholars have conducted relevant research on wireless network planning. Wen *et al.* presented a wireless channel model on the ground of deep learning technology to address the challenges of wireless network planning in railway systems. It updates the neural network parameters online by using Kalman filter to predict the outage probability. The outcomes showcase that the model could effectively forecast wireless propagation with low computational cost and improve the accuracy and efficiency of railway network planning [17]. In order to achieve high reliability, low latency and low cost network planning for industrial wireless mesh networks, three different algorithms have been proposed by Chen Q and other researchers. These algorithms are on the ground of the principles of shortest hop count, least number of routers and balance between shortest hop count and least number of routers for network deployment respectively. Simulation results show that these three algorithms have significant performance advantages [3]. Researchers such as Meng D proposed a data-driven intelligent planning model on the ground of UAV routing network IoT for UAV mobile environment. The model considers factors such as fast response, limited budget and uncertain signal fading. The outcomes showcase that the proposed method can effectively respond to natural contingencies and find the optimal planning solution with limited budget and uncertain signal fading [9]. Meng *et al.* researchers proposed a data-driven intelligent planning model on the ground of UAV routing network IoT for UAV mobile environment. The model considers factors such as fast response, limited budget and uncertain signal fading. The outcomes showcase that the proposed method could effectively respond to natural contingencies and find the optimal planning solution with limited budget and uncertain signal fading [13].

In summary, spatial-temporal analysis and DM techniques have been applied in many fields, and there are many ways to apply them to the field of wireless network planning, but there are fewer studies that apply spatial-temporal analysis and DM techniques to wireless network planning. Therefore, this study applies spatial-temporal analysis and DM techniques to wireless network planning, which is expected to fill the research gap of the combination of the three and facilitate the advacement of the wireless network planning field.

3 Design of Wireless Network Planning Models Integrating Spatio-Temporal Analysis and Data Mining

For better planning the wireless network, a base station human traffic prediction model on the ground of spatial-temporal analysis is proposed in this section, and a new wireless network planning model is designed by integrating DM techniques on the basis of this prediction model.

3.1 Prediction Model for Base Station Foot Traffic Based On Spatio-Temporal Analysis

Network resource optimisation and planning require an understanding of the footfall distribution from a spatial-temporal perspective in order to bridge the gap between theoretical models and the real situation [7, 12]. In order to establish the human flow model, this study utilises the obtained Long Term Evolution (LTE) base station basic information data and the trajectory data of users accessing the network. By analysing the relationship between the change of people flow within a base station and the interaction of people flow between base stations, the dynamic aggregation and dispersion process of people flow in base stations is described from both time and space perspectives with the base station coverage as a unit area. In addition, this study also establishes a prediction model for BTS foot traffic by extracting the spatial and temporal characteristics of BTS foot traffic distribution, which improves the previous prediction methods and enhances the prediction accuracy and usage efficiency. The prediction framework of the constructed base station people flow prediction model is shown in Figure 1.

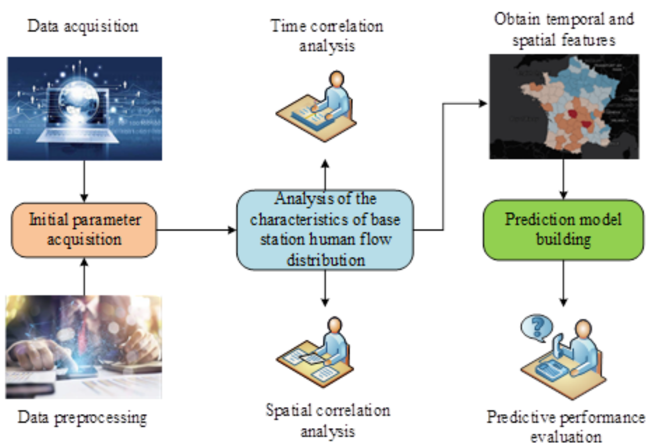

Figure 1: Base station human traffic prediction method framework

As shown in Figure 1, for network resource optimisation and planning, it is first necessary to statistically analyse and clean the data to obtain complete and usable data. Then, the spatial and temporal influencing factors of people flow distribution are analysed from both time and space perspectives, and relevant features are extracted to establish a prediction model. Finally, evaluation metrics are utilized for testing the prediction accuracy of the model. In this study, by analysing the characteristics of historical base station user distribution and the law of user transfer between base stations, the spatial-temporal features of human flow distribution are extracted with base station human flow interaction as the core factor, and the base station human flow prediction model is established. The study first collects the user's access trajectory data and the basic information data of the base station, and the information mainly includes the location and time of the user's access to the base station, as well as the latitude and longitude of the base station. By analysing the collected data, we can visually observe the change information of the user accessing the base station over time and the spatial information of the user's movement. Among them, the relevant calculation of the total activity of the base station is showcased in Equation (1).

$$R_{eNB}^t = \frac{\sum_{A_k^t=1} eNB_k}{n} \tag{1}$$

In Equation (1), R_{eNB}^t denotes the total BTS activity; t denotes the access time; n denotes the total number of all BTSs; eNB_k denotes the kth BTS, and A_k^t denotes the BTS activity. In addition, the relevant calculation of the total user activity of a base station is shown in Equation (2).

$$R_{user}^t = \frac{\sum C_{swich}^t}{m} \tag{2}$$

In Equation (2), R_{user}^t denotes the total user activity of the base station; m denotes the total quantity of users connected to the base station; $\sum C_{swich}^t$ denotes the quantity of active users of the base station. Before establishing the people flow prediction model, it is necessary to analyse the influencing factors of the people flow distribution of the base station from the perspectives of time and space, and extract the corresponding spatial and temporal characteristics. The time factor can consider specific time periods, dates, seasons, etc., while the spatial factor can include the traffic around the base station, commercial areas, residential areas, etc. The modelling is carried out through the temporal factor, the expression of which is shown in Equation (3).

$$T(t_1) = A * \sin(2\pi t/24) \tag{3}$$

In Equation (3), A denotes amplitude and t_1 denotes time. Modelling by spatial factors, the expression is shown in Equation (4).

$$S = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \cdots + \beta_n * X_n \tag{4}$$

In Equation (4), S denotes the footfall of base station, $(X_1, X_2, \cdots, X_n)$ denotes the spatial factor around the base station, and $(\beta_0, \beta_1, \cdots, \beta_n)$ denotes the linear regression coefficient. Combining the time and space factors, the spatial-temporal features can be further extracted. Quantifying the footfall of the base station as the average value per hour and combining the time and space factors yields Equation (5).

$$F(t_1, X_1, X_2, \cdots, X_n) = T(t_1) * S \tag{5}$$

In Equation (5), F denotes the characteristics of people flow. Through the above modelling process, the spatial-temporal features extracted on the ground of time and space influencing factors can be obtained and used to build the people flow prediction model. The base station people flow prediction model constructed in this research is shown in Figure 2.

From Figure 2, it can be seen that the foot traffic of eNB_k in the time period of t_z is influenced by the number

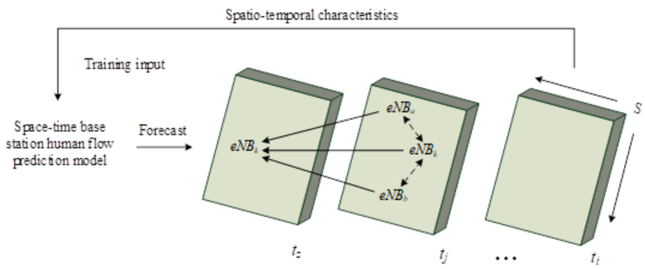

Figure 2: Space-time prediction model of base station human traffic

of users of t_j in the previous time period and the direct interaction with the surrounding base stations eNB_a and eNB_b. The expression of the final trained BTS traffic prediction model is shown in Equation (6).

$$\begin{aligned} N_k^{t_s} &= \sum_{t=t_i}^{t_j} f(N_k^t) + \sum_{p=1}^{l} f'(N_k^{t,s-p}) \\ &\quad + \sum_{t=t_i}^{t_j}\sum_{h=1}^{n} \varphi(C_{h\leftrightarrow k}^t, C_{eNBh,eNBk}^t, L_{hk}^t) \\ &\quad + \sum_{t=t_i}^{t_j}\sum_{h=1}^{n'} \psi(F(N_h^t), L_{hk}^t) \end{aligned} \tag{6}$$

In Equation (6), t_z denotes the forecasting time period. To measure the performance of the prediction model, the accuracy of its prediction was assessed using Root Mean Square Error (RMSE) as shown in Equation (7).

$$RMSE^{t_z} = \frac{1}{n}\sum_{h=1}^{n}[(N_h^{t_z} - \bar{N}_h^{t_z})^2]^{1/2} \tag{7}$$

In Equation (7), $N_h^{t_z}$ denotes the predicted footfall of the base station eNB_h on the time period t_z; $\bar{N}_h^{t_z}$ denotes its real footfall, and the smaller the value of $RMSE^{t_z}$, the higher the prediction accuracy of the model and the better the prediction effect.

3.2 Design of Wireless Network Planning Model Based on Data mining

Random Phase Multiple Access (RPMA) is a low-power wide area network (Low Power Wide Area Network, LPWAN) wireless communication technology [19]. RPMA has several performance advantages over other LPWAN technologies [6]. However, network planning faces great challenges due to the high density of RPMA base stations and uneven service distribution. DM is a process of discovering potential patterns, associations, laws, and knowledge from large amounts of data in an automated or semi-automated manner. The purpose of DM is for revealing the potential value in data and helping people make more informed decisions and strategic planning [8, 15]. Aiming at the problems of high density of RPMA base stations and uneven service distribution, this research proposes a DM-based network planning method for RPMA low-power WAN networks. Figure 3 shows the specific scenario of this research.

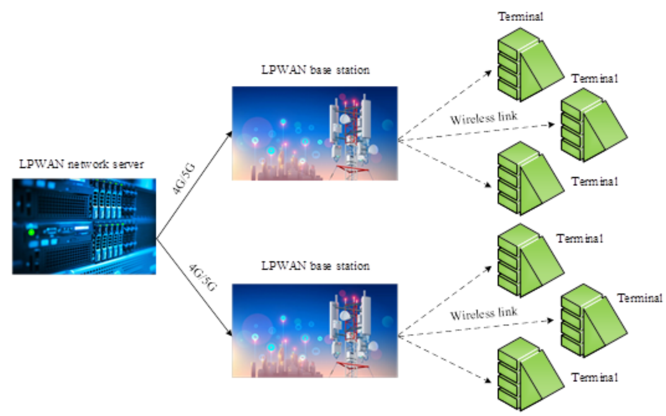

Figure 3: RPMA star network topology

An RPMA network is a typical star topology in which multiple terminals are connected to neighbouring RPMA base stations via wireless connections. The base stations are responsible for receiving uplink data from the terminals and aggregating the data to their respective backhaul connections for multiple data collection and forwarding. The topology of the RPMA network can be represented by Equation (8).

$$N_1 = n_2 * (n_2 - 1)/2 \tag{8}$$

In Equation (8), N_1 denotes the number of base stations in the RPMA network, while n_2 denotes the number of terminal devices in the network. In addition, in order to optimise the coverage quality of the network, the study establishes a mapping relation in the signal quality and the factors, and uses machine learning algorithms to train the data model for forecasting the signal quality and adjusting the base station sites. The expression of this mapping relationship is shown in Equation (9).

$$SQ = f(X_1, X_2, \cdots, X_n) \tag{9}$$

In Equation (9), SQ denotes the signal quality, and $(X_1, X_2, \cdots, X_n)$ denotes the factors affecting the signal quality. The communication link between the network server and the base station is established through 4G 5G backhaul, and the network server mainly handles the tasks of the medium access control layer, including base station management and selection, elimination of duplicate packets, and process confirmation. Aiming at the characteristics of RPMA network, this research proposes a network planning method on the ground of DM. The specific flow of the method is shown in Figure 4.

On the ground of the network planning methodology shown in Figure 4, this study collected measured data

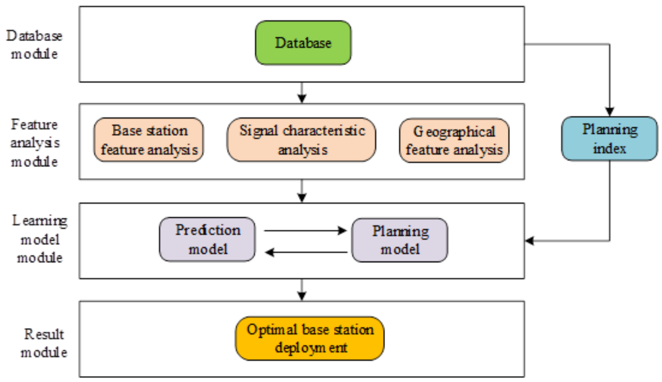

Figure 4: Data mining based network planning approach

from the RPMA network, which was cleaned and analysed. Duplicate and missing values were removed during the cleaning for ensuring the accuracy and completeness of the data. Next, the relevant features affecting the signal coverage quality are extracted, and the base station deployment map is finally obtained through the training of a learning model. This learning model includes a prediction model and a planning model. The prediction model is used to predict the coverage under the network topology and its relevant detail is showcased in Equation (10).

$$Y = f(X) \tag{10}$$

In Equation (10), Y denotes the coverage and X denotes the relevant features. The planning model determines the appropriate base station deployment location on the ground of the prediction results, and its expression is shown in Equation (11).

$$Z = g(Y) \tag{11}$$

In Equation (11), Z denotes the base station deployment location. The overall goal of network planning is to gradually reduce the areas of poor signal coverage so that the coverage quality is close to the required standard. In this study, the weak coverage problem in the wireless network is analysed from the coverage objective, focusing on optimising the coverage blind and weak coverage areas. And the base station location was adjusted according to the network coverage to satisfy the required coverage effect. Weak coverage mainly results from insufficient received signal strength, in affected by factors such as base station side factors, signal transmission path and interference. For addressing the issue, the study trains a data model by using machine learning algorithms to predict the signal quality, and make adjustments to the base station site on the ground of the prediction outcomes. For optimizing the BTS site, this research defines an objective function, which takes into account the factors such as coverage area, weak coverage area and human traffic, and its expression is shown in Equation (12).

$$O = w_1F_1 + w_2F_2 + w_3T_1 \tag{12}$$

In Equation (12), O denotes the target result; F_1, F_2, and T_1 denote the coverage area, weak coverage area, and human flow, respectively, and w_1, w_2, and w_3 denote their corresponding weights, which are used to balance the importance of different factors. By working on, the areas with poor signal coverage will be gradually reduced and the coverage quality will be close to the required standard. This will not only improve the user's network experience, but also enhance the stability and reliability of the network. Wireless network planning is an important issue in the field of communication, and traditional methods only consider network topology and signal coverage, lacking the analysis of spatial-temporal characteristics and user behavior. A model that integrates spatial-temporal analysis and DM can more accurately predict the base station foot traffic and provide optimisation strategies. The specific operation flow of this wireless network planning model is shown in Figure 5.

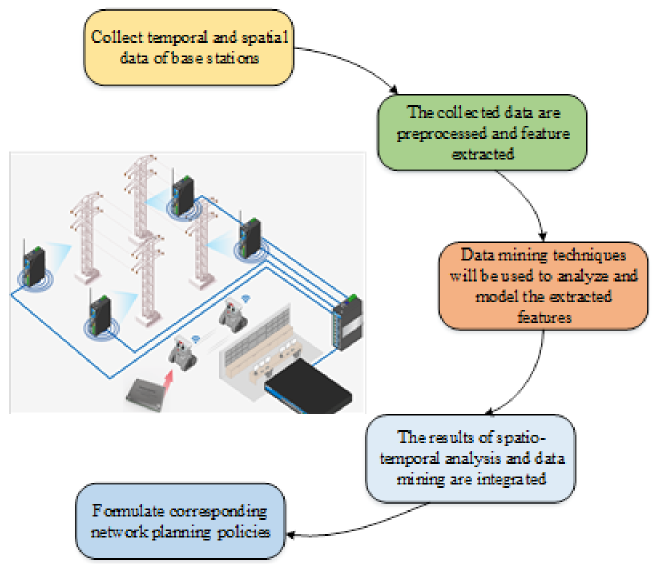

Figure 5: The specific operation flow of the wireless network planning model proposed by the research

Figure 5 indicates that in this wireless network planning model, spatial-temporal data of the base station, including location, human traffic and user behavior, need to be collected first. Then, the data are preprocessed and feature extracted to ensure data quality and integrity. Next, DM techniques such as clustering, classification and prediction are used for analysis and modelling. Finally, spatial-temporal analyses and DM results are fused to develop network planning strategies. Base station placement is performed on the ground of clustering results, optimisation strategies are adopted on the ground of classification results, and future changes in foot traffic are considered on the ground of prediction results.

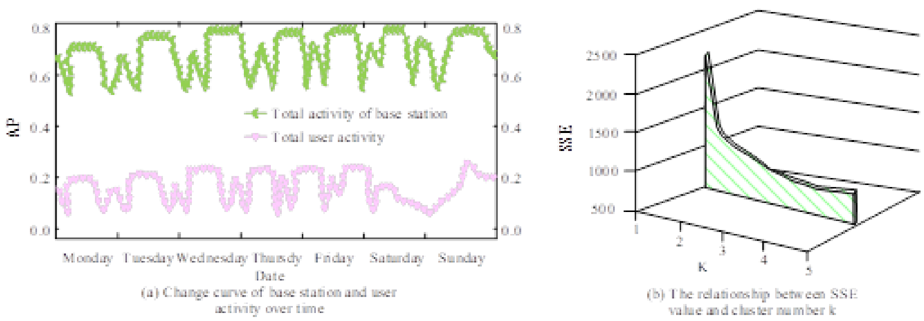

Figure 6: Analysis results of temporal and spatial correlation of selected data

4 Analysis of Model Performance Testing Based on Spatio-Temporal Analysis and Data Mining

For analyzing the effectiveness of the practical application of the crowd prediction model and the wireless network planning model proposed by the study, the study tests the two models through comparative experiments in this chapter, and the test results show the superiority of the novel model on the ground of spatial-temporal analysis and DM proposed by the study.

4.1 Comparative Analysis of the Effectiveness of Crowd Forecasting Models

In order to better analyse the performance of the footfall prediction model, the study first analyses the spatial-temporal correlation of the selected data. After that, the model is then compared and analysed with the SARIMA model in terms of mean square error, prediction accuracy, mean absolute error and R-square. The results of this study on the spatial-temporal correlation analysis of the selected data are shown in Figure 6.

Figure 6(a) shows that the total base station activity and total user activity change almost synchronously in time, and the correlation coefficient is 0.69. This verifies the strong correlation between the base station foot traffic distribution and the interaction between foot traffic base stations. According to the base station clustering method, the activity distribution of each base station is clustered, and Figure 6(b) demonstrates the change of SSE with the increase of k value, and k = 3 is chosen as the best clustering result. This means that base stations within the same cluster have similar people changes at the same time, and that people changes occur between base stations to generate people interactions, which verifies that the inter-base station interactions of people flows are spatially localised. Therefore, spatial influence features should be considered to be extracted from the localised space during model construction. The results of the mean-square error of the two models in predicting the pedestrian flow in one day are shown in Figure 7.

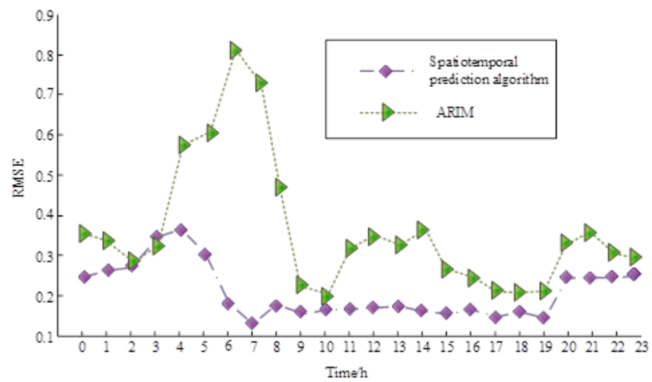

Figure 7: Comparison of RMSE predicted by the two models on a random day

Figure 7 shows the curves of the RMSE values of the two methods over time. As can be seen in Figure 7, at each time period, the RMSE values of the footfall prediction model are lower than those of the ARIMA model. The largest difference between the RMSE values of the two prediction models is found at 7:00 a.m. on that day, when the RMSE value of the ARIMA model reaches 0.81, while the RMSE value of the research-proposed prediction model reaches 0.12. This result indicates that the research-proposed footfall prediction model performs better than the ARIMA model as a whole, and that during the time periods when the footfalls interact with each other more than with the ARIMA model, the prediction method performs significantly better than the ARIMA model. Afterwards, the prediction accuracy, average absolute error and R-square index of the two models are compared at each time point, and the comparison outcomes are shown in Table 1.

Table 1 demonstrates that the prediction accuracy of the proposed spatial-temporal analysis human flow prediction model outperforms that of the SARIMA model in all time periods, and its average prediction accuracy in

Table 1: Comparison results of each index of the two models at different time points

Point in time	Spatiotemporal analysis model			SARIMA model		
	Prediction accuracy (%)	Mean absolute error	R-squared	Prediction accuracy (%)	Mean absolute error	R-squared
1	81.3	0.12	0.86	69.3	0.35	0.69
3	82.5	0.09	0.85	70.5	0.33	0.71
5	85.7	0.13	0.84	69.8	0.29	0.70
7	90.1	0.11	0.85	70.3	0.36	0.68
9	88.6	0.10	0.87	68.9	0.41	0.70
11	87.3	0.08	0.86	71.2	0.28	0.72
13	85.8	0.12	0.88	70.6	0.31	0.71
15	88.2	0.09	0.84	70.2	0.33	0.69
17	83.7	0.10	0.86	69.3	0.34	0.68
19	84.1	0.08	0.83	70.1	0.40	0.69
21	83.5	0.07	0.85	69.9	0.29	0.72
23	82.3	0.08	0.84	69.8	0.33	0.71

one day is 86.2%; the average absolute error value of the spatial-temporal analysis human flow prediction model in all time periods is 0.10, which is also significantly better than that of the SARIMA model, which is 0.33.Lastly, it can be found in Table 1 that the average R-squared value of the spatial-temporal analytical footfall prediction model has an average R-squared value of 0.85, which is closer to 1 than the SARIMA model's 0.70, indicating better performance. Comparing the above dimensions, it can be found that the overall prediction performance of the proposed spatial-temporal analysis human flow prediction model is better than the comparison model.

4.2 Performance Analysis of Data Mining Based Signal Prediction Model for RPMA Low Power WAN Networks

For testing the performance of the proposed network signal prediction model of the study, the study conducts error performance comparison experiments with ARIMA signal prediction model. In addition, it is also compared with ARIMA signal prediction model and ARMA signal prediction model for prediction classification performance comparison experiment. The results of the error performance comparison between the proposed signal prediction model and ARIMA model are shown in Figure 8.

From Figure 8(a), the prediction errors of the proposed signal prediction model are balanced at 0.035 and 0.040 in the training and test sets. Figure 8(b) demonstrates that the prediction error of the ARIMA signal prediction model is balanced at 0.093 and 0.011 in the training and test sets. This outcomes exhibit that the proposed signal prediction model of the study outperforms the ARIMA signal prediction model in terms of the prediction error dimension. Afterwards, the prediction classification results of the three signal prediction models are collated to plot the clustering results shown in Figure 9.

Figure 9 demonstrates that the predicted clustering results of the proposed signal prediction model are tighter and closer to the actual situation compared to the clustering results of the other two models. Therefore, it illustrates that the prediction performance of the proposed signal prediction model outperforms the comparison models. Combining the above two dimensions, it can be clearly found that the performance of the proposed signal prediction model outperforms that of the same type of prediction model, and its application to the wireless network planning model can improve the planning effect of the model.

4.3 Comparative Performance Analysis of Wireless Network Planning Models Based on Spatio-Temporal Analysis and Data Mining

In this study, a base station traffic prediction model on the ground of spatial-temporal analysis and a signal prediction model on the ground of DM are constructed, and finally a new wireless network planning model is presented on the basis of the two. For analyzing the practical application effect of the proposed wireless network planning model (Model 1), the study compares its performance with the network topology model (Model 2) and the capacity planning model (Model 3). The study applies the three models to real-world planning and uses specific expert evaluations of each of their metrics to compare and analyse the performance of each metric. The results of the expert panel's evaluation of the coverage, capacity, and delay metrics of the three models are showcased in Table 2.

As can be seen from Table 2, the expert group's evaluation of the indicators of coverage, capacity and delay for Model 1 is generally good, with most indicators being excellent and only a few being good. From the evaluation

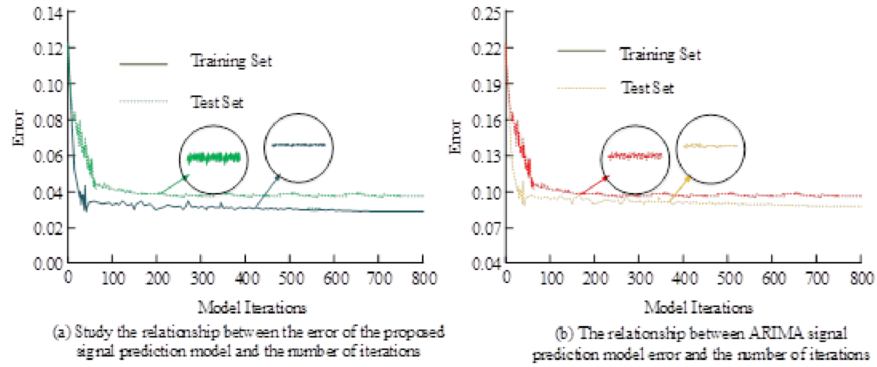

Figure 8: Comparison results of prediction error performance of the two models

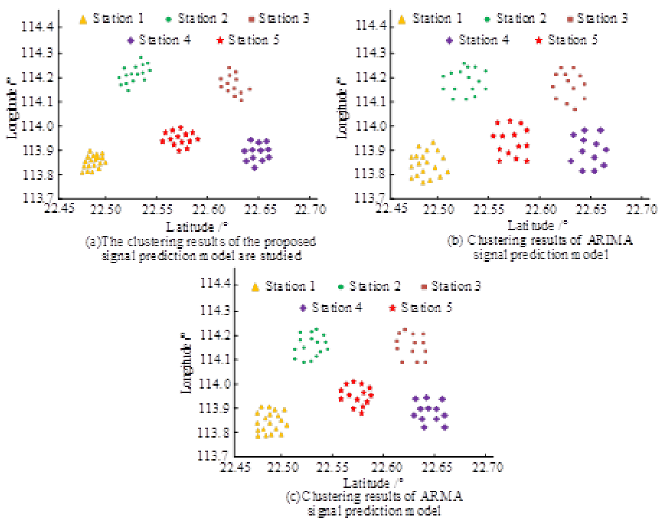

Figure 9: Prediction clustering results of three signal prediction models

results of the expert group on Model 2 and Model 3, most of the indicators are good, and a small number of indicators have poor evaluation results. Therefore, in terms of coverage, capacity and delay dimensions, the overall performance of Model 1 outperforms the comparison models. Afterwards, the specific scores of the experts on signal quality, cost-effectiveness of Model 1 and Model 2 are plotted in Figure 10.

As can be seen from Figure 10, the specific scores for each indicator of signal quality and reliability for Model 1 exceed those for Model 2, and among the scores for each indicator of signal quality, the expert scores the highest for the BER indicator of Model 1 at 8.9, which is higher than that of Model 2 at 7.8, and among the scores for each indicator of reliability, the expert scores the highest for the operating cost of Model 1 at 9.0, which is higher than that of Model 2 at 7.7. Score. In summary, the performance of the wireless network planning model on the ground of spatial-temporal analysis and DM proposed in the study is better than the comparison models, and its practicality is stronger. In addition, in order to further verify the network security performance of the proposed model, Model 1 is compared with the wireless network planning model based on dynamic programming (Model 4), the wireless network planning model based on machine learning (model 5) and the wireless network planning model based on data mining (model 6). The encryption performance, anti-interference ability, intrusion detection and defense of the four models are tested and compared, and the comparison results are shown in Table 3.

The encryption performance in Table 3 represents the throughput of the model when encrypting transmitted data; The anti-interference ability represents the signal retention ability of the model under interference. Intrusion detection rate represents the proportion of network intrusion successfully detected by the model. The false positive rate represents the proportion of normal network activity that the model incorrectly identifies as an intrusion. As can be seen from Table 3, model 1 is superior to the comparison model in various network security performance indicators, and its anti-interference ability, intrusion detection rate, encryption performance and false positive rate are -78.6dBm, 96.5%, 150.2Mbps and 1.8%, respectively, which are all at an optimal level. The above results show that the proposed model 1 has certain advantages in improving the performance of network security.

5 Conclusion

Aiming at the poor performance of the current wireless network planning model, the study proposes to integrate spatial-temporal analysis techniques and DM techniques into the wireless network planning model to propose a new wireless network planning model. An empirical analysis of the proposed new wireless network planning model shows that the model performs mostly well in terms of coverage, capacity and delay, which is significantly better than the comparison model. The expert scoring of the model against the comparison model showcases that the BER and reliability scores of the model are 8.9 and

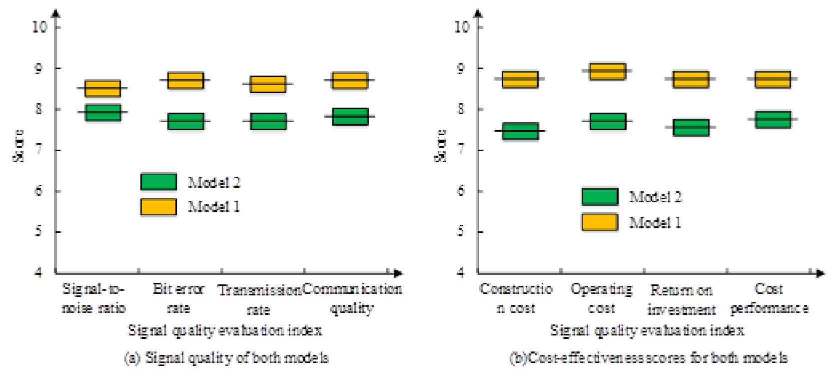

Figure 10: The specific scores of the experts on signal quality, cost-effectiveness of Model 1 and Model 2

Table 2: Comparison of evaluation grades of coverage, capacity and delay of the two models

Contrast index		Model 1	Model 2	Model 3
Coverage rate	Signal strength	Optimal	Good	Good
	Signal quality	Optimal	Bad	Good
	Signal coverage	Good	Good	Bad
Capacity	Network throughput	Optimal	Optimal	Good
	Average user speed	Good	Good	Good
	Network resource utilization	Optimal	Bad	Optimal
Time delay	E nd-to-end delay	Good	Good	Bad
	Transmission delay	Optimal	Good	Good
	Queue delay	Optimal	Good	Good

Table 3: Comparison results of network security performance indicators of the four models

Type of model	Anti-interference capability (dBm)	Intrusion detection rate (%)	Encryption performance (Mbps)	False alarm rate (%)
Model 1	-78.6	96.5	150.2	1.8
Model 4	-70.5	91.2	141.2	3.3
Model 5	-68.6	88.5	138.8	3.5
Model 6	-66.5	87.6	136.4	4.1

9.0, which are significantly higher than those of the comparison model, which are 7.8 and 7.7. In addition, it is also found that the anti-jamming ability, intrusion detection rate, encryption performance and false positive rate of the proposed model are -78.6dBm, 96.5%, 150.2Mbps and 1.8%, respectively, which are superior to the comparison model. The above results show that the model not only provides good signal quality, but also has high safety performance. This achievement provides a strong guarantee for the safe operation of wireless network, and also provides a new idea and direction for the future development of wireless network planning.

Acknowledgments

This work was supported by 2023 Annual Key Research Project of Higher Education Institutions in Henan Province: Research on the Construction of an Informationization Platform for Professional Development in Higher Vocational Colleges Based on the "Sydney Accord" Paradigm (NO.23B520041).

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